Cost-Effective Localization in Underground Mines Using New SIMO/MIMO-Like Fingerprints and Artificial Neural Networks

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***Abstract*—Safety measures have always been a main concern in the mining industry that, despite the modern practices, utilizes old-fashioned surveillance and monitoring systems. Our mission in underground mines stems from the profound need of geo-positioning systems that can accurately localize endangered miners and their heavy machinery in one of Earth's most harsh and rough environments. In underground mines, complex channels' responses to wireless transmitted signals challenge traditional localization techniques, yet they fail to defeat our innovative, cost-effective and accurate fingerprint-based positioning techniques that use artificial neural networks (ANNs) and exploit space-time diversity. Being among the pioneers in underground communications research, we bring forward a more sophisticated and accurate fingerprint-based positioning technique that exploits spatial transmission diversity in the presence of more than one transmitter T_x and/or receiver R_x antenna, such as in the case of single/multiple input multiple output (SIMO/MIMO) communication systems. More importantly, an advanced study is conducted to reduce the cost of fingerprint-acquisition trading off pinpoint accuracy for lower complexity and better ANNs' design. By challenging the localization system using less data measurements, we prove that ANNs, when properly designed, succeed to attain high positioning accuracies even when localizing in measurement gaps that were not seen in the training phase.**

***Index Terms*—Indoor localization, underground mines, artificial neural networks, channel impulse response, fingerprinting, time diversity, spatial diversity, SIMO, MIMO, cooperative/collaborative localization.**

I. Introduction

Indoor localization in complex channels is as yet a topic of research that aims to replicate the success achieved by commercially viable outdoor localization systems. In the mining industry, for example, localizing miners and their heavy machinery is not a luxurious task, but a critical requirement that guarantees basic safety measures and helps avoid potential risks in cases of fire, collapses and other hazardous work activities. In fact, localization techniques that succeed to attain high positioning accuracies in outdoor scenarios fail to maintain similar precision and accuracy in underground mines. In position estimation theories, major parameters extracted from wireless signals, such as the received signal's strength (RSS), time of arrival (ToA), angle of arrival (AoA) and/or time difference of arrival (TDoA), are used to estimate the distance travelled by wireless signals from transmitters to receivers. However, complexity arises when the channel, where wireless transmission takes place, introduces robust distortion, attenuation and/or fading to received signals' characteristics. In complex indoor channels such as the case in the mining environment, *a priori* estimation of complex channel's response to wireless transmission is not yet feasible due to the severe reflections/refractions that signals suffer from due to rough surfaces, water, inter-connected tunnels and heavy machinery in the confinement of underground galleries.

Major research projects at Telebec's Underground Communications Research Laboratory (LRTCS), one of the leading research laboratories in the world for underground communications (cf. surveys [1] and [2]), have revealed new, more accurate indoor localization techniques that use fingerprinting and ANNs in the 2.4 GHz, 5.4 GHz [3], [4], over UltraWide Band (UWB) [5], [6] and recently being investigated in the mmWave/60 GHz bands [7]. Localization using fingerprinting and ANNs is based on extracting parameters from the channel impulse responses (CIRs) and mapping them to given positions located at different distances away from a given transmitter [8]. In order to overcome some of the challenges, such as the presence of inter-connected tunnels, and to further enhance localization accuracy, more sophisticated fingerprint-based positioning techniques were developed in [9], [10] and [11] by exploiting spatial, temporal and spatio-temporal diversities, respectively.

In this work, we put forward a new fingerprint-based positioning technique that exploits the presence of dual T_x and R_x antennas in nowadays SIMO/MIMO-capable communication equipment. It is shown herein that CIR-based localization exploiting spatial diversity and SIMO/MIMO-type fingerprints significantly increases positioning accuracies and is, so far, the most accurate among all CIR-based fingerprint positioning techniques in underground mines. More importantly, all studied fingerprint-positioning techniques are challenged by lower fingerprint-acquisition rate in the ANNs' training phase. In an effort to reduce measurement campaigns' cost, ANNs are well-designed and trained to attain high positioning accuracies even when they are forced to localize in measurement gaps that, due to the lowered fingerprint-acquisition rate, were never introduced to ANNs' training phases.

In the following section, we review the most recent CIR-based positioning techniques that exploit spatially and/or temporally diverse fingerprints in underground mines. Section III introduces the novel fingerprint-based localization technique that exploits SIMO/MIMO-type fingerprints. An advanced study is then performed to lower the cost overhead of fingerprint-acquisition in section IV after which performance results are presented in section V. Finally, the paper is closed by a conclusion in section VI.

II. Localization in Underground Mines using CIR-based Fingerprinting

The special nature of underground mines shown in Fig. 1, which is made of quasi-curvilinear intersecting tunnels, enforces the quest to develop more sophisticated localization techniques seeking better security and safety practices in the mining industry. For more than fourteen years of continuous research, LRTCS and similar research labs have been looking for alternatives to traditional triangulation techniques before the first ANN-based geo-location method was innovated and published in [8]. In the following, we study, as a background exercise, the method in [8] laying the groundwork for discussing more advanced techniques that exploit space-time diversities in [9], [10] and [11].

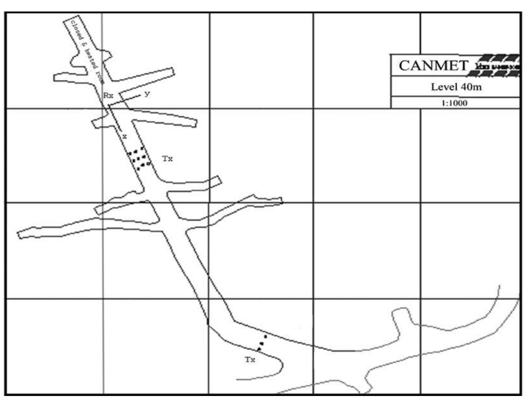

Fig. 1 – Map of the tunnel.

A. ANNs and CIR-Based Fingerprint Positioning

Fingerprint positioning techniques rely on mapping wireless signals' parameters to the distance separating the receiver from the transmitter. Due to the special nature of underground propagation channels, some parameters such as the RSS fluctuate for the same position inside the mine and may not be used solely for position estimation [12]. The same can be said about AoA and ToA, because the former (i.e., AoA) represents the last angle of reflection inside the tunnel while the latter (i.e., ToA) represents the total time travelled after bouncing inside the confined tunnel. In [8], a fingerprint is a combination of seven parameters which 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).

By using Multilayer Perceptron (MLP) ANNs, which are extremely powerful computational models for non-linear problems, a fingerprint $f_i = (\bar{\tau}, \tau_{rms}, \tau_{max}, P, N, P_1, \tau_1)$ is then matched to its corresponding set of distances $D = \{d_1, d_2, d_3, ..., d_n\}$. For simplicity, the distance is calculated using the $x - axis$ only neglecting minor variations which are of less importance on the $y - axis$ inside the confinement of narrow underground tunnels as shown in Fig. 2. The original memoryless technique (i.e., ANN(1,0)), developed in [8] and used as a comparison benchmark, scores an accuracy of 1.3 m and 1.4 m for 90% of the training and testing data, respectively.

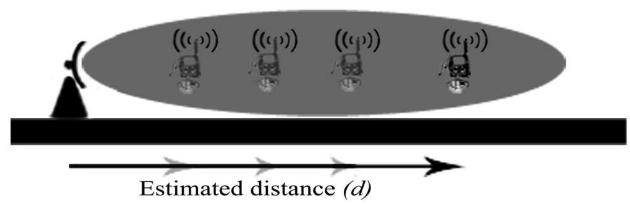

Fig. 2 – The CIRs are extracted at different distances to the transmitter with 1-meter step-size along the x-axis.

B. Exploiting R_x Spatial, Temporal and Space-Time Diversities

At first, the localization technique in [8] was challenged by misleading information about the direction of transmission in case one localizing receiver is placed at junctions of interconnecting tunnels. To overcome such scenarios and to further enhance positioning accuracy, a new fingerprint-based positioning technique was developed in [9] and it exploited R_x spatial diversity at two receivers as shown in Fig. 3. A centralized ANN, shown in Fig. 4, is then used to collect both signatures (or sub-fingerprints) from both receivers, R_1 and R_2 separated by a distance D = 80 m, forming one fingerprint that contains 14 parameters. The training set S that defines

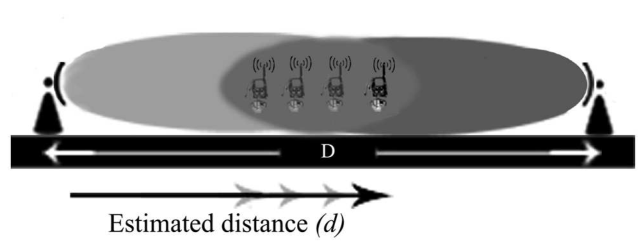

Fig. 3 – Localization using two signatures of two receivers in the area where two signals intersect.

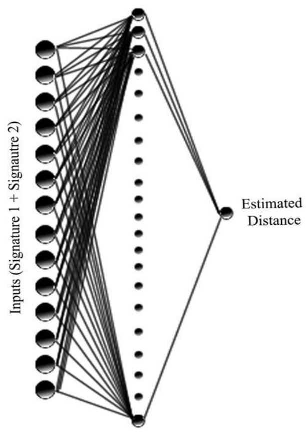

Fig. 4 – Neural network based on multiple signatures.

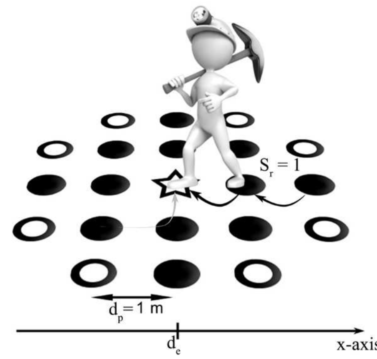

Fig. 5 – Possibilities of previous positions for $l = 3$.

the fingerprints' space is a concatenation of two sub-sets, S^{R_1} and S^{R_2}, and is denoted by: $S = \{F_1, F_2, F_3, ..., F_m\} = \{(f_1, f_1'), (f_2, f_2'), (f_3, f_3'), ..., (f_m, f_m')\}$, where f_i and f_i' represent the sub-fingerprints collected, for a position i, at R_1 and R_2, respectively. By using one ANN with two sub-fingerprints from R_1 and R_2, localization accuracy significantly increases to prove the effectiveness of exploiting R_x spatial diversity and errors slip to 77 cm and 90 cm for the training and testing data, respectively.

Increasing the accuracy and robustness using R_x spatial diversity only may require increasing the number of access points which is not an option in the limited space of underground mine tunnels. However, the use of temporal diversity increases the system's accuracy when more than one fingerprint is concatenated in time slots prior to estimating the transmitter's final position at $d_i^{t_0}$ [10]. A temporal fingerprint is represented by:

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

where l is the memory level or the number of concatenated fingerprints. The length of a temporal fingerprint L_f depends on the memory depth where:

$$L_f = 7l.$$

An example of a temporal fingerprint is demonstrated for $l = 3$ in Fig. 5. The maximum number of path fingerprints j_{max} that may be obtained for a given distance is upper bounded by N_{f_p} where:

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

All possible sub-fingerprint, for $l = 3$, at t_{-1} and t_{-2} are concatenated to the sub-fingerprint at t_0 forming 25 temporal fingerprints (or path fingerprints) each of length L_f = 21. For each memory length l, there exists one ANN that is trained to count for all possible path-fingerprints leading to a given distance d along the x-axis of the tunnel. With a step-size of d_p = 1 m along the x-axis of the tunnel, the miner's possible path fingerprints may be extracted from the CIRs at the filled-circled positions in Fig. 5. For simplicity, motion across diagonals is excluded. Multiple scenarios were tested for different memory levels (i.e., l = 1, 2, 3, 4) and their position estimation errors start at 89 cm and 1.14 m, at $l = 2$, and drop down to 48 cm, at $l = 4$, for 90% the training and testing data, respectively.

After maximizing accuracy gains of temporally diverse fingerprints, a new fingerprinting technique was developed in [11] and it uses both R_x spatial and temporal diversities of the collected fingerprints. By exploiting R_x spatial diversity from both collaborative receivers and combining memory-type fingerprints, the developed localization system topped the accuracy benchmark, surpassing those achieved by previous fingerprint-based techniques in [8], [9] and [10]. The fingerprint subset $S_i^{R_1}$, collected at at a distance d_i away from R_1, is concatenated pathwise with the second fingerprint subset $S_i^{R_2}$ collected at R_2, where: $S_i^{R_1} = \left\{F_i^{R_1,1}, F_i^{R_1,2}, F_i^{R_1,3}, ..., F_i^{R_1,j_{max}}\right\}$, $S_i^{R_2} = \left\{F_i^{R_2,1}, F_i^{R_2,2}, F_i^{R_2,3}, ..., F_i^{R_2,j_{max}}\right\}$. The spatio-temporal fingerprint subset S_i extracted for one specific distance d_i is designed as follows:

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

The dynamic design of spatio-temporal fingerprints allows variable memory depths ranging between $l = 1$ (no memory) and $l = 5$ (beyond which no increased performance is noticed) reproducing multiple spatio-temporal fingerprint scenarios that we donate by (l_1, l_2). Each receiver, R_1 or R_2, can be set to introduce any memory depth, l_1 or l_2, respectively. At lower complexity, a spatio-tempral ANN performing at ($l_1 = 2, l_2 = 2$) is capable of achieving performance accuracies of less than 50 cm, at S_x = 1 m, which matches the results obtained by a complex memory-assisted ANN performing at $l = 4$ in the presence of one receiver only. It will be shown later in Sec. V-B that at higher S_x, long chains of memory-type fingerprints become less significant while spatio-temporal techniques maintain a better posture at lower fingerprint sampling rate. Results of other scenarios involving different memory allocations (i.e., ANN(2,1), ANN(3,1), etc ...) at each receiver may be reviewed in [11].

III. Exploiting Tx and Rx Spatial Diversities: SIMO/MIMO-type Fingerprint Positioning

So far, we discussed R_x spatial diversity (i.e., at two receivers R_1 and R_2) and temporal diversity (i.e., using memory) showing how they are both used to design new fingerprint-based positioning techniques. Although their performance results, as shown later in Sec. V, are outstanding in terms of positioning accuracy and precision, we push their performance limits forward and introduce a more advanced fingerprint positioning technique that exploits the presence of dual T_x antennas [1]. In addition to that, the novel technique simultaneously uses R_x spatial diversity which significantly increases localization performance. SIMO-type fingerprints are formed from sub-fingerprints of two adjacent T_x antennas in the presence of one receiver or R_x. A SIMO-type fingerprint is denoted by:

$$F_i^{SIMO} = (f_i^{Tx_1}, f_i^{Tx_2}),$$

Where $f_i^{Tx_1}$ and $f_i^{Tx_2}$ are fingerprints collected, at a position i, by Rx_1 for Tx_1 and Tx_2, respectively. On the other hand, MIMO-type fingerprints are concatenated by extracting two T_x sub-fingerprints at both receivers Rx_1 and Rx_2. A MIMO-type fingerprint is represented as:

$$F_i^{MIMO} = \left\{ (f_i^{Tx_1}, f_i^{Tx_2}), (f_{i'}^{Tx_1}, f_{i'}^{Tx_2}) \right\},$$

where $f_i^{Tx_1}$ and $f_i^{Tx_2}$ represent sub-fingerprints collected at Rx_1, whereas $f_{i'}^{Tx_1}$ and $f_{i'}^{Tx_2}$ are sub-fingerprints extracted by Rx_2, at a position $i' = D - i$, for Tx_1 and Tx_2, respectively.

The use of SIMO/MIMO-type fingerprints is so far the most robust CIR-based localization technique with accuracies that drop below 50 cm as shown later in Sec. V. By comparing both SIMO/MIMO-like fingerprints and spatio-temporal fingerprints, many conclusions may be drawn. First, T_x spatial diversity comes as an alternative to memory-type sub-fingerprints that result from exploiting temporal diversity, leading to lower system complexity and better design efficiency in the scenarios where transmitters are equipped with two T_x antennas. Second, as we discuss further in the following section, temporal diversity fingerprints prove to produce lower performance when measurement gaps are introduced in an effort to reduce the cost of measurement campaigns. However, localization using T_x and R_x diversities maintains low position estimation errors even when the resolution of fingerprint-acquisition is reduced.

IV. Complexity and Cost Reduction

Fingerprinting techniques are mainly criticized because they require extensive measurement campaigns that are costly and time consuming. What if the measurement campaigns' cost can be cut down to less than one quarters of its original value? Would localization techniques, which based their fingerprints on CIRs exploiting space and/or time diversities, hold as accurate and cost-effective positioning techniques for underground mines? A study was conducted to answer the reasonable questions in an effort to tune pinpoint accuracies and trade it for lower fingerprint-acquisition cost. By introducing measurement gaps or sub-grids that are not fed to the ANNs in the training phases, we challenge all CIR-based localization techniques and test their positioning accuracies and precision at higher sampling step-size S_x[2]. ANNs are carefully designed

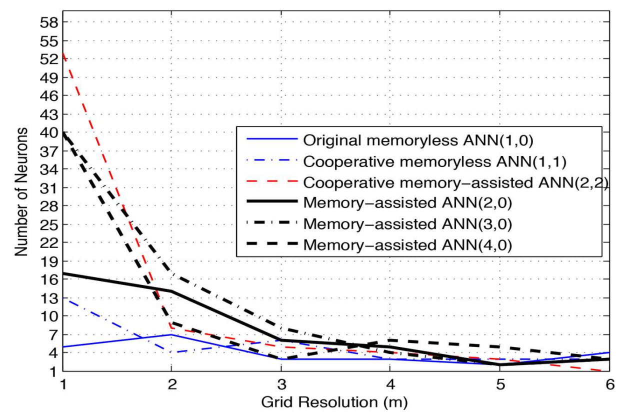

Fig. 6 – Optimum number of neurons for different ANNs.

to interpolate measurement gaps by running trial and error simulations that aim to optimize the number of neurons needed for each S_x. For each localization technique and S_x, a trial is run three times while varying the number of neurons n as follows:

$$1 < n_n < N_n = 2N_i + 1,$$

where N_i is the number of inputs fed to the ANNs which varies depending on the spatial, temporal or spatio-temporal fingerprints' chain length. As shown in Fig. 6, the number of neurons drops with the decrease in the number of fingerprints for each training set which comes as a result of cutting down the cost (i.e., reducing the measurement campaign's acquisition rate).

V. Performance Results

The performance results of CIR-based localization techniques are presented using the cumulative density function (CDF) that shows, on one axis, the accuracy of position estimations in meters, and on another, the precision accomplished by a given localization technique. It should be noted that all ANNs are trained on 75% of the collected fingerprints while leaving 25% for the testing phase at S_x= 1 m. In the case where $S_x \geq 2$ m, training results represent 75% of the sampled sub-grid then ANNs are tested using 25% of every sub-grid not seen in the training phase. All spatial, temporal and spatio-temporal positioning techniques are analyzed at S_x = 1 m

[1] Real measurements taken every 0.5 m and 1 m along the y-axis and x-axis simulate dual antenna spacing of $\delta_y^{Tx} = 0.5$ m and $\delta_x^{Tx} = 1$ m , respectively.

[2] S_x, ranging from 1 m to 6 m, represents the step-size between consecutive offline measurement positions along the x-axis of the tunnel.

first, after which they are compared, at 90% precision, using different sampling grid's resolution in Figs. 7, 8 and Tab. I.

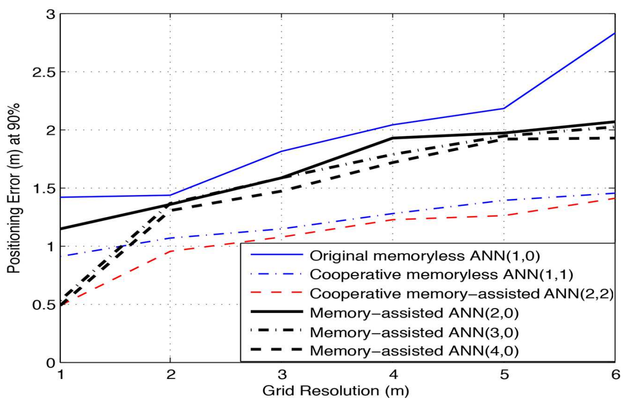

Fig. 7 – Positioning errors from CDFs of testing data at 90% precision.

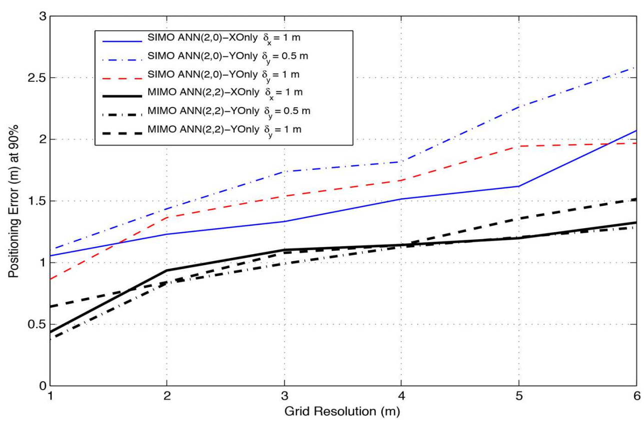

Fig. 8 – Positioning errors from CDFs of SIMO/MIMO-type testing data at 90% precision.

A. *Results of SIMO/MIMO-Type Fingerprinting using Tx and Rx Spatial Diversities*

SIMO/MIMO-type fingerprints, discussed in Sec. III, constitute the groundwork for a new, more sophisticated and less complicated type of a CIR-based fingerprint positioning technique. They bring in the advantages of exploiting spatial diversity at both the receiver and transmitter, without introducing memory, raising positioning-accuracy levels to a new record in underground mines. Since we have one T_x-antenna separation distances at the x-axis and two at the y-axis, we shall report them separately using the notations $\delta_x^{Tx} = 1$ m, $\delta_y^{Tx} = 1$ m and $\delta_y^{Tx} = 0.5$ m, respectively. SIMO-type fingerprints are denoted by $2Tx$-$1Rx$ whereas MIMO-type fingerprints use the $2Tx$-$2Rx$ notation and their performance results are reported in Fig. 8 and Tab. I.

If we compare, at $S_x = 1$ m, SIMO-type techniques to ANN(2,0) that uses the same fingerprint length of $L_f = 14$, we notice that SIMO-type fingerprints localize more accurately with a an estimation error of 85 cm as compared to 1.15 m using memory-assisted techniques with ANN(2,0). Another example can be drawn from comparing spatio-temporal diversity, such as ANN(2,2), to the accuracy of MIMO-type fingerprints using $2Tx$-$2Rx$ ANN. While the first uses temporal diversity to boost accuracy results to 49 cm, the latter (i.e, using MIMO-like fingerprints) succeeds to score accuracies of 43 cm and 38 cm at $\delta_x^{Tx} = 1$ m, $\delta_y^{Tx} = 0.5$ m, respectively. The use of SIMO/MIMO-like fingerprints surpasses the performance limits achieved by temporally diverse fingerprints and provides a less complex fingerprinting technique that does not include memory when localizing transmitters in underground mines. It is also beneficial to state the importance of having R_x and T_x diversities at the same time when localizing at lower sampling resolution or higher S_x as discussed in the following section.

B. *Results of Low Fingerprint-Acquisition Rate on Accuracy*

The pinpoint accuracies obtained from fingerprint localization exploiting R_x and/or T_x spatial, temporal and spatio-temporal diversities, reported above, may be controlled and traded off for lower fingerprint-acquisition cost. Location accuracies at $S_x \geq 2$ m provide less fingerprints in the training phases of ANNs and reduces the time needed for offline fingerprint-acquisition. More than 14k ANNs were tested in this simulation in the best effort to optimize the number of neurons used for each CIR-based localization technique and the significant results are shown in Fig. 6. In the following, we shall judge each localization technique based on its ability to sustain the benchmark obtained by the original technique ANN(1,0) developed in [8] which, at S_x = 1 m , which has an estimation error of 1.42 m 90% of the time (circled in Tab. I).

After selecting the most effective number of neurons based on S_x from Fig. 6, we show the performance accuracies of all localization techniques using higher step-sizes of S_x = 3 m and S_x = 6 m in Figs. 9 and 10. The rest of step-size scenarios are shown for 90% precision in Figs. 7 and 8 then summarized in Tab. I to show the granularity of positioning accuracies for different T_x antenna spacing or δ^{Tx}. The performance

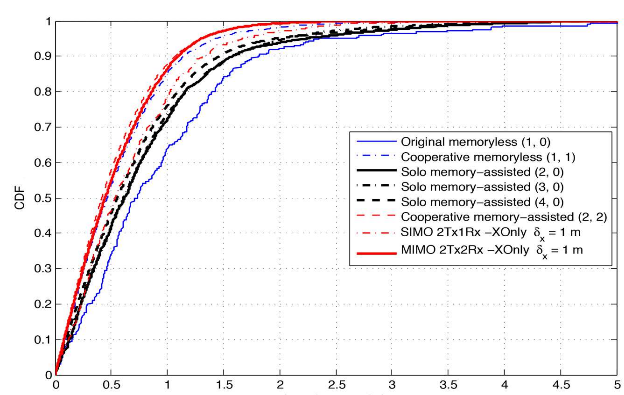

Fig. 9 – Localization performance at S_x = 3 m.

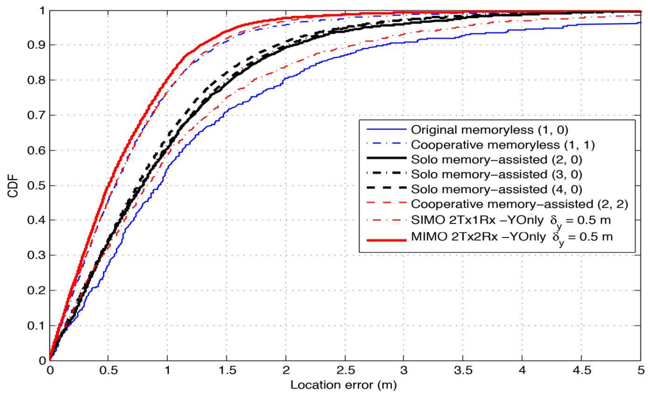

Fig. 10 – Localization performance at S_x = 6 m.

of temporal fingerprints was expected to degrade at lower sampling resolution (i.e., higher S_x) because temporal sub-fingerprints, collected at positions separated by higher step-sizes, carry less information about the position to be estimated. An example can be drawn from the performance of ANN(4,0) which fails to sustain the 1.42 m accuracy beyond S_x = 2 m.

However, taking a closer look at the results of memory-assisted localization techniques that only exploit R_x spatial diversity reveals an outstanding performance for ANN(2,2) which achieves, at S_x = 6 m, an accuracy matching the benchmark of 1.42 m obtained by ANN(1,0) at S_x = 1 m! The same can be said about ANN(1,1) which can maintain the benchmark using only one fifth of the measurement campaign's data (i.e., at S_x = 5 m).

The new positioning techniques that use SIMO/MIMO-like fingerprints reveal the power of combining R_x and T_x diversities in the realm of fingerprint positioning using ANNs in underground mines. The use of SIMO-type fingerprints exploiting spatial diversity at T_x only is not the best candidate for localization because it reports lower accuracy performance compared to ANN(1,1) which uses R_x spatial diversity only.

TABLE I – Performance Results with Multiple Resolution

ANN Technique	Grid Resolution Accuracy Results					
	1 m	*2 m*	*3 m*	*4 m*	*5 m*	*6 m*
ANN(1,0)	1.42 m	1.44 m	1.81 m	2.04 m	2.12 m	2.83 m
ANN, 2Tx1Rx $\delta_y^{Tx} = 0.5$ m	1.10 m	1.43 m	1.73 m	1.81 m	2.26 m	2.58 m
ANN, 2Tx1Rx $\delta_y^{Tx} = 1$ m	0.85 m	1.36 m	1.53 m	1.66 m	1.94 m	1.97 m
ANN(2,0)	1.15 m	1.35 m	1.58 m	1.92 m	1.97 m	2.07 m
ANN(3,0)	0.53 m	1.36 m	1.58 m	1.78 m	1.94 m	2.02 m
ANN(4,0)	0.48 m	1.30 m	1.46 m	1.72 m	1.91 m	1.93 m
ANN, 2Tx1Rx $\delta_x^{Tx} = 1$ m	1.05 m	1.23 m	1.33 m	1.51 m	1.61 m	2.07 m
ANN(1,1)	0.91 m	1.07 m	1.15 m	1.28 m	1.39 m	1.45 m
ANN, 2Tx2Rx $\delta_y^{Tx} = 1$ m	0.64 m	0.84 m	1.07 m	1.14 m	1.35 m	1.51 m
ANN(2,2)	0.49 m	0.95 m	1.07 m	1.22 m	1.26 m	1.41 m
ANN, 2Tx2Rx $\delta_x^{Tx} = 1$ m	0.43 m	0.93 m	1.10 m	1.14 m	1.19 m	1.32 m
ANN, 2Tx2Rx $\delta_y^{Tx} = 0.5$ m	0.38 m	0.83 m	0.98 m	1.12 m	1.20 m	1.28 m

However, the performance limits of MIMO-like fingerprints exploiting both T_x and R_x diversities surpass those of the original techniques, especially at $\delta_y^{Tx} = 0.5$ m highlighted in Tab. I, to achieve location accuracies of 38 cm and 1.28 m for the testing data at S_x = 1 m and S_x = 6 m, respectively. One can cut down the cost of data measurements to half by using S_x = 2 m and still obtain positioning accuracies of 83 cm 90% of the time! Localization using MIMO-like fingerprints in the presence of well-designed ANNs proves to be an accurate, robust and cost-effective technique in underground mines.

VI. Conclusion

The focus of this study stems from years of research for an accurate, cost-effective positioning techniques that can improve safety practices in underground mines. The new fingerprint positioning technique, presented here, uses MIMO-like signatures that combine R_x and T_x spatial diversities and brings forward new positioning accuracies of less than 50 cm, at sampling step-size S_x = 1 m, while achieving high accuracy records of 1.28 m when ANNs are challenged, in the training phases, using only one sixth of the measurement campaign's fingerprints (i.e., at S_x = 6 m). When correctly applying the discussed ANNs' design strategies, localizing using MIMO-type fingerprints turns out to be, as yet, the most accurate and cost-effective CIR-based positioning technique and it may be implemented using different wireless technologies in underground mines.

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