Distributed Radio Positioning for Personnel Tracking in Coal Mine Tunnels

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Abstract: Received signal strength-based positioning and tracking of humans is a reliable solution for harsh indoor environments like the longwall tunnels at underground coal mining sites. The mining personnel with radio tags on their body can be tracked along a line of sensing reference nodes. The wired bus backbone for the transmission of all sensor data to a central processing station is the limiting factor for the system’s coverage. To extend the 1D coverage up to the kilometers range, we present a distributed localization approach with data compression mechanisms. Therefore, the bus is divided into hierarchical subnets with connecting gateway devices. The positioning accuracy, being dependent on the size of the subnets, is analyzed using simulation results which are based on empirical signal strength values. One mayor achievement of the distributed approach is a nearly unchanged positioning accuracy as the most significant system evaluation criterion. Copyright © 2015 IFSA Publishing, S. L.

Keywords: Distributed computing, Personnel tracking, Radio positioning, Received signal strength.

1. Introduction

The establishment of an active protection system for the monitoring of personnel in underground coal mines is crucial to save human lives and therefore, is an essential part of the development strategy of leading mining companies. The objective for an indoor local positioning system (ILPS) is to cover the whole area with the same quality of service, determined by the average positioning accuracy.

In underground coal mines, three different mining methods are used which define the structure of the mining area. Cut-and-fill mining, room-and-pillar mining and longwall mining [1]. Longwall mining is used if the coal seam has a large and thin shape. This specialized type of mining process is characterized by minimal manual handling and highly productive automated control systems.

For longwall mining, the complexity of the self-advancing mining equipment, e.g. the electro-hydraulic shields for ceiling support, is a mortal danger for the present maintenance staff. A direct remote positioning [2] for the longwall application using the received signal strength (RSS) of radio signals is shown in Fig. 1. The developed system for this exemplary “MineLoc” scenario, will be described briefly in the following.

A set of fixed reference nodes (RNs) receive the RF packets of mobile blind nodes (BNs) and transmit the corresponding RSS values to a central data concentrator [3]. For the data backbone, the well-known and failsafe CAN bus is used. It offers line-
topologies up to the kilometers range and data rates up to 1 Mbit/s [4]. At the data concentrator, the user positions are calculated and used to intervene in the control system of the mining process and stop regarding shields.

Fig. 1. MineLoc system for Indoor radio positioning and personnel tracking in underground longwall coal mining using direct remote positioning (20 users along 300 m).

The number of shields which have to be blocked depends on the accuracy and availability of the localization system. The localization accuracy is dependent on the reference node density and thus, is indirect proportional to the achievable coverage. Since a certain accuracy is required for a productive mining, the maximum distance between the reference nodes is limited, e.g. to a few meters for sub-meter accuracy [3]. For the used CAN bus, the maximum number of nodes on a bus segment is limited to 32 due to bus load constraints of typical transceiver circuits [4]. Assuming a reference node clearance of 1.5 m, this means an overall system coverage of only 4.65 m which is not sufficient for the 300 m longwall application, shown in Fig. 1.

To break up the dependency between the two criteria accuracy and coverage, we proposed a distributed weighted centroid localization (dWCL) strategy with a hierarchical sensor data field bus in [5]. In the current paper, we enhance the proposal by a survey of common indoor positioning sensor techniques in Section 2 and investigate the accuracy limits of RSS-based positioning.

In Section 3, the basic centroid localization and the weighted centroid localization algorithms are derived for the 2D scenario. The underlying radio propagation model and consequential accuracy issues are analyzed in Section 4, in particular for the propagation in tunnels. In Section 5, the localization system’s coverage is deduced from the CAN specification, addressing practical CAN cable lengths and data rates for centralized and distributed location estimation strategies. The distributed weighted centroid localization (dWCL) approach is presented in Section 6. In Section 7, we compare the centralized and distributed localization performance using a 1D tracking simulation. In Section 8, the results are discussed and investigated in terms of an outlook for further system developments.

2. Survey of Indoor Positioning Sensors

The latest ILPS research activities for the tracking and navigation of people and objects show a variety of applied sensor technologies [6]. The main evaluation criteria are the accessible coverage and accuracy of the position estimations. An overview of available technologies with a taxonomy according to these two criteria is shown in Fig. 2. Of course, also other criteria like costs for installation and maintenance, the scalability, the user acceptance and specific system limitations should be taken into account. A further taxonomy of localization techniques and system implementations according to all these criteria are proposed in [8] and [9].

Magnetic systems with artificial quasi-static magnetic fields are robust in multi-path environments, although the high power consumption of coil-based magnetic field transmitters limits the field of application and especially the system coverage [10]. Another class of magnetic systems exploits the disturbances of the Earth’s magnetic field due to structural steel elements of buildings, where the sensor values are spatially varying but temporally stable [11].

Optical navigation and positioning systems, using monocular or stereo camera systems or range imaging sensors, reach good accuracies in the sub-centimeter range but are limited to the use inside static and predefined environments [12].

Ultrasound systems use time of flight (TOF) measurements for distance approximations between deployed nodes. For line-of-sight (LOS) scenarios inside one room, the systems reach an accuracy of a few centimeters [13]. The use of directional sensors...
like infra-red (IR), ultrasound or optical systems is limited to LOS scenarios.

Radar as a typical device-free radio-based positioning system is applicable for the tracking of moving objects or users. Round-trip time (RTT) and angle of arrival (AOA) principles are used to determine the range and the direction between the radar transceiver and obstacles, reflecting the radar signals [14]. The average accuracy is in the lower centimeter range while an area of 10 m to 100 m can be covered [15]. The main drawback of radar systems is the required LOS between transceiver and tracked object. For the majority of indoor applications, e.g. the exemplary MineLoc tracking application, one has to consider non-line-of-sight (NLOS) conditions.

Radio frequency signal evaluations at fixed access points (APs), e.g. using narrow-band 2.4 GHz ISM radio, are also possible in NLOS environments. Lateration based on TOF or received signal strength (RSS) measurements as well as AOA methods reach accuracies around several meters, depending on the environment’s obstruction level, the desired coverage and the number of APs. RSS fingerprinting systems like Horus [16] or RADAR [17] need a time-consuming precalibration phase to build the reference data base. In addition to the number of APs, the number of training data sets strongly influences the accuracy. Since RF signals propagate with the speed of light, high precision timer modules are required for precise TOF measurements. As described in [18], a time quantization of 150 MHz is required to achieve an accuracy of 1 m when using the time of arrival (TOA) technique. With time difference of arrival (TDOA), a synchronization is only required among the receiving anchor nodes.

Radio frequency identification (RFID) techniques are used for smaller systems with a coverage at room level for active RFID and sub-meter coverage for passive RFID [19]. Beside RSS lateration and fingerprinting, the limited communication range of RFID devices is used for the cell of origin (COO) positioning principle. Depending on the used technique and the node density, the accuracy ranges between some decimeters and several meters.

Ultra-wideband (UWB) systems use a short pulse width to overcome the issue of multipath propagation for a precise TOF measurement. The high temporal resolution of the UWB channel impulse response enables the solution of multipath components of the received signal. I.e., it is possible to reach high range resolutions with 5 cm accuracy when using TOF techniques to estimate the first path of the received signal [20]. The main drawbacks of the technique are the limited communication range and the rare availability and high costs of the transceivers.

Hybrid approaches with the additional aid of an inertial measurement unit (IMU) are typically used for pedestrian navigation in mixed indoor / outdoor positioning scenarios. Due to the latest advances in micro-electro-mechanical system (MEMS) integration, the use of a miniaturized IMU is interesting for low-cost ILPS solutions. Accuracy and coverage of an IMU-aided hybrid positioning system are relatively high but strongly depend on the problematic long-term stability of the IMU orientation. Additional information might be used to compensate positioning errors due to the IMU orientation drift, e.g. detailed floor plans of the building [21] or zero velocity update (ZUPT) mechanisms [22]. An approach for a more robust sensor fusion uses a tight integration of two systems by an extended Kalman filter, e.g. the fusion of RFID-based RSS measurements and a foot-mounted IMU [23].

3. Weighted Centroid Localization

A position estimation based on centroid computations uses information from a reference infrastructure to estimate the position of one or more mobile blind nodes. In general, the known positions of fixed reference nodes are weighted and aggregated to estimate the position \( P_i(\tilde{x}, \tilde{y}) \) of the \( i^{th} \) blind node according to

\[
P_i(\tilde{x}, \tilde{y}) = \frac{\sum_{j=1}^{m} w_{ij} B_j(x, y)}{\sum_{j=1}^{m} w_{ij}}
\]

where \( w_{ij} \) is the weight for the link between the \( i^{th} \) blind node and the \( j^{th} \) reference node and \( B_j(x, y) \) is the reference node's known position in a 2D Cartesian coordinate system. Compared to fine-grained localization approaches (e.g. maximum likelihood estimator), the centroid requires no expensive search for a maximum of a function but only one approximative calculation.

The basic CL algorithm as a range-free implementation uses binary link information of several RNs with known positions as sensor metric for a rough position estimation [24]. In Fig. 3(a), a scenario with four RNs is shown.

![Fig. 3. Principle of centroid (CL) and weighted centroid localization (WCL) approach. Mobile blind node's position (red dot) is estimated relative to the position of four reference nodes (black triangles).](image)

a) Basic CL   b) WCL, low RSS   c) WCL, high RSS

Assuming entirely uniform circular communication ranges, the BN is located inside the shaded area when it has a link to three of the four RNs. For the exemplary scenario, the lower left RN has no link to the BN. Thus, it does not take part in the centroid
The position of the $i$th BN is calculated according to (1) where the weights are given by

$$
w_{ij}(CL) = \begin{cases} 1, & \text{link to } j\text{-th RN} \\ 0, & \text{no link to } j\text{-th RN} \end{cases}$$

(2)

The general weighted centroid localization (WCL) approach makes use of a certain link quality indicator to get more precise position information. The nature of the LQI is not restricted. It might be any information about the distance between transmitter and receiver, e.g., an RSS indicator (RSSI) value from several RNs [25]. Also the hop-count in wireless sensor networks (WSNs) with multi-hop protocols might be used [26]. In the case of range-based WCL based on RSS values, those will be first transformed into distances according to an appropriate path loss model. The Euclidean distance between the $i$th BN and the $j$th RN is written as $d_{ij}$. For the average value of the distance-dependent RSS, the log-distance model according to (5) is used. Rearranged to $d_{ij}$ it can be written as

$$
d_{ij} = 10^{\frac{\text{RSS}_{ij} - A_p}{10\eta_p}}$$

(3)

where $\text{RSS}_{ij}$ is the measured RSS between the $i$th BN and the $j$th RN, $\eta_p$ is the path loss exponent and $A_p$ is the RSS intercept value, here given for a RX-TX separation of $d = 1 \text{ m}$. In the next step, the distances $d_{ij}$ are transformed into weights $w_{ij}$ according to

$$
w_{ij} = \frac{1}{(d_{ij})^g},$$

(4)

where $g$ is the WCL weighting factor. The value of $g$ depends on the environmental conditions and the topology of the reference nodes [27]. The BN's position is given by the weighted centroid of the RNs' positions using (1).

The accuracy of WCL strongly depends on the subfield of the area (center or border) and the relationship between relative and absolute LQI values. The relationship is influenced by the RN density and the RSS resolution. Since the RSS is usually given by the receiver's 8 Bit RSSI with 0.5 dB resolution and the nature of RSS shows a logarithmic decay with linear increasing distance, the resolution over the distance is not linear. As it is indicated in Fig. 3(b), the low RSS values near to the receiver's sensitivity level (e.g., -94 dB) have a much lower resolution than high RSS values. 0.5 dB will correspond to a few centimeters for short distances while for large distances, 0.5 dB will equate to a few meters [28]. As indicated in Fig. 3(b), for low RSS values, the BN's position is dominated by one RN. For high RSS values, the advantage of the range-based weighting gets lost and the WCL reaches similar results compared to CL. Thus, an appropriate RN infrastructure setup is very important to achieve an accurate and efficient WCL estimation [29-30].

There exist several improvements of centroid localization. They all aim at a minimization of the algorithm's systematic (biased) error, e.g., at the edge of the covered environment.

In [31], the adaptive WCL (AWCL) approach is proposed. AWCL makes the estimation more independent from the communication range and the placement of the RNs. The weights are adapted according to the relative differences in RSS values of all receiving RNs. When the relative difference is low, e.g., for overall low RSS values, all the weights are reduced by a certain value. Thus, the relative difference in RSS values will rise and the higher influence of one dominating RN, e.g., the top right RN in Fig. 3(b), will lead to a lower estimation error for positions near to the center of the regarding environment.

A further adaption of the weights according to the selective adaptive WCL (SAWCL) principle is proposed in [32]. The SAWCL can be seen as an extension to AWCL, where not only a reduction of all weights but also an increase of the weights is realized to handle the systematic error behavior of WCL. Furthermore, the reduction and increase factors are not set constant and the transition from reduction to increase is gradually. The severity of the adaption depends on the distribution of the weights across all RNs. The aim of SAWCL is to include the additional information of a uniform RN setup for an increased position estimation accuracy. The weights are increased when the BN is located in a distant position to all RNs and thus, no RN shows an outstanding weight. The weights are reduced when the BN position is near to one RN and thus, the regarding RN has a large weight compared to all other weights.

The relative span exponential weighted localization (REWL) approach, proposed in [33] also uses weight adaptions to increase the influence of RNs which are close to the BN. A comparison of REWL and WCL using indoor RN setups with varying number of nodes is given in [27]. The WCL with difference of estimated distances (WCL-DED) algorithm, proposed in [34], uses the degree of estimated distance difference to adapt the WCL weighting factors. The shape-based centroid localization (SBCL) approach differentiates between different cell areas like corner cell, center cell or edge cell [35]. The topological knowledge of the RN placement is used to improve the estimation accuracy of the native centroid localization. In [36], we propose a refinement of the WCL position estimates instead of the weight refinements. Here, only one computation is necessary during the online positioning. The main computational effort is transferred to an offline preprocessing phase.
4. Radio Signal Strength Model

The nature of RF propagation limits the accuracy of an RSS-based ranging in several ways. First of all, the distance resolution decreases with increasing distance. Most RF protocols have not been designed for the purpose of RSS-based ranging for positioning. The RSS should be the same over a large area in terms of a steady quality of service for RF communication systems. For ranging purposes, the RSS as the range sensor metric should enable a certain distance resolution.

In general, the distance-depending average path loss shows a logarithmic dropping of power with a linear increasing distance as given in Fig. 4.

The log-distance path loss model [37] is used to describe the average power at the receiver:

$$PL(d) = PL(d_0) + 10n_p\log\left(\frac{d}{d_0}\right)$$

The average path loss PL(d) (in dB) over a LOS distance d between transmitter (TX) and receiver (RX) is given by the reference path loss PL(d_0) over a reference distance d_0 and the environment-specific propagation coefficient n_p.

As stated earlier, a typical RSS resolution of 0.5 dB leads to a distance resolution of a few centimeters for small distances (< 2m). For large distances (> 20m), the given RSS resolution leads to a distance resolution of several meters [28]. Thus, only small distances are useful for an RSS-based ranging.

A further limitation is given by large-scale and small-scale signal fading, introduced by multipath propagation (reflection, diffraction, scattering) and shadowing effects. The path loss curves in Fig. 4 show extensive small-scale fading for medium ranges. Interestingly, the number of deep signal fades diminishes for larger distances, which can be ascribed to waveguide effects.

For the application of personnel tracking in longwall mining the environment can be seen as a tunnel with a nearly rectangular cross-section (Fig. 5). When the height and the width of the tunnel are small (compared to the length) it can be regarded as an over-sized imperfect waveguide. The propagation will exhibit the guided wave characteristics and the propagation loss can be even smaller than in free space [38].

For indoor environments with a dominating LOS component, the fast fluctuations are modeled with a Rician distribution [39]. In [1], experiments with 450 MHz and 900 MHz support the theoretical waveguide model. The fast fluctuations are only apparent in the field near the transmitting antenna. As the frequency increases, the fast fluctuating region is prolonged.

Since the waveguide effect is larger for smaller wavelengths, the general large scale behavior of an increasing path loss for larger frequencies does not hold in tunnel environments. The waveguide acts as a high pass filter, so signals with higher frequency attenuate slower. This effect is examined in [1] and also by our experiment results in a narrow corridor. In Fig. 4, we compare the resulting path loss for 2440 MHz and 868 MHz. For comparison, both graphs are matched to the same reference path loss $\mathcal{A}_p = -67$ dBm. For 2440 MHz, the path loss shows a slighter dropping than for 868 MHz. For distances above 20 m, the path loss is even lower than the LOS path loss for free-space propagation.

To sum up the influence of indoor radio propagation on the accuracy of RSS-based ranging and positioning, in particular for a 1D environment like mining tunnels, we propose the following guidelines and statements: First, the larger frequency has a better communication range which is non-intuitive when looking at outdoor and open space indoor radio propagation. Second, the channel bandwidth should be chosen as large as possible to suppress small-scale fading. Third, for a proper RSS resolution, the distance between the mobile BN and the reference nodes shall be limited. This also limits the clearance $D$ between the RNs and the overall coverage of the system.
5. Sensor Data Bus Load Limitations

One solution for an increased system coverage without increasing the number of RNs is to lower the RN density by means of increasing the RN-RN clearance D. As shown in Fig. 6, the accuracy will degrade for larger values of D.

The results can be divided into different regions. For \( m < 5 \), the quadratic WCL gives the best accuracy. For \( m = 5 \), quadratic WCL and WCL with \( g = 2.4 \) achieve a similar accuracy with \( RMSE = 9.69 \text{ m} \). For \( m = 5 \) and \( g = 4.0 \), the accuracy is worse, indicated by the higher value of \( RMSE = 13.01 \text{ m} \). For \( m > 5 \), the WCL estimate with \( g = 2.4 \) will be more accurate than quadratic WCL, reaching an accuracy with \( RMSE = 0.41 \text{ m} \) for 98 RNs and \( RMSE = 0.20 \text{ m} \) for 196 RNs. The RMSE as a function of \( m \) and \( g \) is shown in Fig. 9.

For the given 1D RN topology, the optimum weighting factor is relatively insensitive to the RN-RN clearance. The main conclusion for the longwall mining ILPS with a target accuracy of \( RMSE = 0.5 \text{ m} \) and \( \sim 300 \text{ m} \) coverage is the need of a certain number of RNs. With 98 RNs, the RN-RN clearance is approximately \( D = 3 \text{ m} \), resulting in a RMSE below the target value. This configuration represents a good trade-off between the evaluation criteria cost and accuracy. Since the given RMSE values only reflect the systematic error of WCL, the RN-RN clearance has to be kept even lower.
5.2. CAN Bus Load and Positioning Coverage

As can be seen from Fig. 6, the coverage is not only limited by the electrical CAN bus load but also by the data bus load. The correlation of CAN cable length, positioning coverage and CAN data rate will be analyzed in the following, considering the peculiarities of the longwall mining environment.

The CAN bus is a typical wired backbone used in noisy industrial environments. It offers line-topology and data rates up to 1 Mbit/s [4]. The maximum bus load – comprising cable length, data rate and connected nodes – is given by the network specifications like cable attenuation and the electrical load of a single CAN transceiver. Taking into account the electrical bus load and the data bus load, for the centralized ILPS solution, a maximum number of 20 BNs can be located simultaneously along a line of up to \( m = 31 \) reference nodes (RNs) [3].

To define the region which can be covered by the reference infrastructure, it is necessary to make some assumptions, which are given by the ISO CAN specification [4] and the surrounding conditions of the underground mining ILPS application.

First, the achievable position estimation accuracy is correlated with the clearance between the reference nodes. The systematic error of WCL position estimates for a 1D RN topology shows an adequate RMSE below 0.5 m for \( D = 3.0 \) m RN-RN clearance. Real-life experiments have shown that sufficient positioning accuracies can be realized with a node clearance of \( D \leq 2.0 \) m [3].

Second, for a suitable mounting, the CAN cable length has to be three times the node clearance. When the clearance between the reference nodes is \( D = 2.0 \) m, each CAN cable between the nodes has to be 6.0 m in length.

Third, without additional time synchronization, a deterministic CAN bus communication without large latencies is feasible with 50% data bus load. Thus, the practical CAN data rate is two times the CAN gross data rate.

Fourth, for a more generalized applicability of the investigations, the maximum number of connected nodes on a single CAN bus is limited to 32. This criterion fits the demands of the electrical bus load constraints using typical high-speed and low-speed CAN transceivers.

With these predefined assumptions and the relationship between CAN cable length and CAN data rate, it is possible to define the maximum coverage of the 1D positioning system (cf. Fig. 10). For the maximum cable length, the CAN Bit timing is the limiting factor. The CAN Bit timing of the connected nodes shows deviations, mainly affected by tolerances of their clock source, e.g. caused by aging and a temperature drift of the oscillators. For a CAN data rate of 500 kBit/s, a time quantum of \( T_Q = 0.125 \mu s \) will lead to a maximum theoretical CAN cable length of 150 m. With additional latencies introduced by the CAN hardware (e.g. CAN controller response time, transceiver delays), the maximum practical CAN cable length has to be smaller than the theoretical value [40]. Corresponding values for practical scenarios are given in Fig. 10.

![Fig. 10. Maximum specified data rate and cable length for CAN bus lines considering typical latencies (bus propagation, CAN transceiver, CAN controller). The shaded area indicates cable lengths, which are not sufficient for the longwall mining ILPS.](image)

The number of RNs, influencing the accuracy, and the number of simultaneously captured BNs affect the required data rate. The net data rate to collect the sensor information from \( n \) BNs using \( m \) RNs is given by

\[
DR_{net} = m \left\lceil \frac{nx}{8} f_{pos} 64 \text{ Bit} \right\rceil
\]

where \( x \) is the number of bytes for each sensor and \( f_{pos} \) is the position update rate. For the CAN gross data rate, no generally valid value exists. The CAN header and inter frame gap have deterministic values. Since the number of stuff bits is dependent on the actual bit stream, the overall number of bits per CAN message is variable. A worst case scenario, derived from the bit timing considerations in [41], leads to

\[
DR_{gross} = m \left\lceil \frac{nx}{8} f_{pos} \left( \frac{34 + 64}{4} + 47 + 64 \right) \text{ Bit} \right\rceil
\]
The practical data rate for a nearly deterministic communication rate depends on the specific application with allocation of more or less high prioritized message identifiers. The maximum tolerated bus load for the given application is 50%. Thus, according to

$$DR_{det} \geq \frac{DR_{gross}}{0.5} \quad (8)$$

the practical data rate is twice the gross data rate.

### 5.2.1. Bus Load for Centralized Computation

The infrastructure components for a centralized WCL computation using a single-level CAN as sensor data backbone are shown in Fig. 11. To meet the bus load constraint, \( m = 32 \) RNs is the maximum infrastructure buildout. The RNs receive RF packets from up to 20 BNs with a position update rate of 2 Hz. The sampled RSS values have 1 Byte resolution and are transmitted to the data concentrator PC using a single CAN bus. An exemplary distribution of the RSS values is shown in Fig. 11 for a single BN located at \( x = 66 \text{ m} \).

[Diagram: Infrastructure components for centralized position estimation of 20 blind nodes (BNs) using RSS values from 32 reference nodes (RNs).]

The net data rate which has to be realized by the CAN backbone can be calculated according to (6). For the given example, the CAN has to offer a minimum of \( DR_{net} = 11.9 \text{ kBit/s} \). Using (7), the theoretical gross data rate has to be larger than \( DR_{gross} = 25.1 \text{ kBit/s} \). As stated above, for an error-free communication, without the suppression of less prioritized CAN packets, the data rate has to be twice as large as the theoretical gross data rate. With \( m = 31 \) RNs and \( n = 20 \) mobile BNs, a practical data rate of \( DR_{det} = 50.2 \text{ kBit/s} \) leads to a specified CAN data rate of \( DR_{CAN} = 125 \text{ kBit/s} \). Looking at Fig. 10, this data rate is not sufficient for the desired 300 m system coverage. Furthermore, the position estimation error will be very high when only 31 BNs are used to cover the corresponding maximum system coverage of nearly 177 m. For an acceptable accuracy, the RN-RN clearance has to be set to \( D \leq 3.0 \text{ m} \). Thus, for the maximum buildout according to the electrical load constraint, the overall system coverage for \( m = 31 \) RNs is limited to 90 m.

The RN-CAN is used to connect \( m = 14 \) RNs to one gateway. With \( m < 32 \), the electrical load is not an issue. Also the data bus load will be much lower than for the exemplary setup from Fig. 11. The required CAN data rate of \( DR_{CAN} = 50 \text{ kBit/s} \) and the corresponding maximum CAN cable length of 1300 m are not limiting the positioning coverage. The maximum length of the RN-CAN depends on the position of the gateway. Close to the first RN in the subnet, an overall CAN cable length of 60 m will be long enough to cover the 14 RNs. This cable length would be short enough for the use of a CAN data rate which is ten times the required data rate.

For the centralized WCL computation without data compression, the PC-CAN would have to offer a minimum of \( DR_{net} = 75.26 \text{ kBit/s} \). The theoretical gross data rate has to be larger than 158.76 kBit/s. This results in a practical CAN data rate of \( DR_{det} = 317.52 \text{ kBit/s} \). For the given scenario, we have to set \( DR_{CAN} = 500 \text{ kBit/s} \) which is defined in the CAN specification. Looking at Fig. 10, this data rate limits the maximum cable length to 130 m.

### 5.2.2. Bus Load for Distributed Computation

To increase to coverage of the positioning system, the distributed RSS positioning uses additional infrastructure components to realize a hierarchical sensor data backbone. Up to 14 gateway devices with two CAN interfaces are used to connect up to 196 RNs to the data concentrator (cf. Fig. 12).

[Diagram: Hierarchical infrastructure for decentralized position estimation of 20 blind nodes (BNs) using 196 reference nodes (RNs), which are connected to the data concentrator over 14 gateways (GWs). Exemplary RSS distribution and position estimation of BN with ID 15, located at \( x = 66 \text{ m} \).]
The embedded gateway architecture is shown in Fig. 13. The CAN bus consists of the two CAN signal lines (CAN high, CAN low) and two supply lines, which are used to power the ICs. The CAN transceiver which is connected to the RNs has a separate 3.3 V power supply and is connected to the Cortex M4 system MCU via opto-couplers. Beside a large set of peripheral components, the MCU contains two dedicated CAN controller. The interface between CAN transceiver and CAN controller uses three wires, one MCU output for the serial TX data, and two MCU inputs for the serial RX data and the CAN interrupt line.

![Fig. 13. Embedded gateway architecture with Cortex M4 system MCU and two isolated CAN interfaces.](image)

With the hierarchical bus concept, the maximum number of reference nodes can easily be scaled according to the application needs. Even though, the maximum cable length of 130 m for the top hierarchical PC-CAN bus subnet limits the system’s coverage to less than 44 m. For the given MineLoc application for the personnel tracking in the underground longwall mining environment, at least 300 m positioning coverage along the line of RNs is required. To obtain a larger coverage, the backbone cable length has to be increased and thus, the backbone data rate has to be decreased by the same order of magnitude. The required data compression for the top hierarchical PC-CAN. Again, the overall system coverage of 433 m is given by 1/3 of the cable length. Compared to the centralized position computation, the coverage of the positioning system is increased by factor 10.

6. Distributed Centroid Positioning

The previously introduced data compression requires a distributed computation of subnet BN positions and the computation of an additional weighting factor, denoting the influence of each subnet position on the final centralized position estimation.

6.1. Distributed Estimation Phase

On all gateways, a 1D subnet BN position is calculated according to the WCL algorithm. The processing steps for the 1D subnet position estimation are the same like for centralized WCL, given in Section 3. Looking at the RMSE as a function of WCL weighting factor $g$ and the number of RNs $m'$, a weighting factor of $g = 2.4$ was found to be the optimum value for the given 1D RN setup (cf. Fig. 9).

The final calculation of the local position $p_i(x)$ of BN $i$ is given by the weighted centroid of all RN positions $B_i(x)$ using

$$p_i(x) = \frac{\sum_{j=1}^{m'} (w_{ij} B_j(x))}{\sum_{j=1}^{m'} w_{ij}}, \{p_i eN | 0 < p_i \leq m'\} \quad (10)$$

This 1D position is rounded to an integer value, representing the ID of the nearest RN. Thus, using $m' = 14$ RNs, the rough position fits in a 4 Bit representation when transmitted to the data concentrator PC. Additionally, the gateways process the RSS values (1 Byte) from all $m'$ connected RNs to compute the weighting factor $v_i$ with 4 Bit representation. The weighting factor $v_i$ is calculated using the average RSS of all $m'$ RNs according to

$$v_i = \frac{S_{min} - \sum_{j=1}^{m'} RSS_{ij}}{S_{min} - A_p}, \quad 15, \quad \{v_i eN | 0 < v_i \leq 15\} \quad (11)$$

where $A_p$ is the reference path loss in a distance of 1 m and $S_{min}$ is the receiver's sensitivity level. The value of $v_i$ is normalized to a range of $0 \dots 15$ to fit into the 4 Bit representation.

6.2. Centralized Estimation Phase

The gateways forward the compressed data of $v_i$ and $p_i(x)$ to the data concentrator PC over
the PC-CAN. On the data concentrator PC, the information from all gateways are processed to calculate the final position \( P_i(x) \) of the mobile BN. The impact of each subnet position \( p_i(x) \) can be adjusted by modifying the weight \( v_i \) according to

\[
v_i' = v_i^k, \quad (12)
\]

where \( k \) is the dWCL (subnet) weighting factor. Thus, it is possible to adapt the position estimation algorithm to different scenarios with varying infrastructure node setups. Beside the node clearance \( D \), the ratio between the overall number of nodes \( m \) and the nodes per subnet \( m' \) has an influence on the optimum value of \( k \).

A weighting of the local subnet positions \( p_i(x) \) according to the average RSS weighting function \( v_i' \) is used to compute the final position \( P_i(x) \) of the mobile BN with ID \( i \) according to

\[
P_i(x) = \frac{\sum_{j=1}^{s} (v_i' p_{ij}(x))}{\sum_{j=1}^{s} v_i'} \quad (13)
\]

7. Large-Scale 1D Tracking Simulation

For detailed investigations of different bus topologies, a simulation of the distance-dependent RSS is better suited, since an empirical evaluation with \( m = 196 \) RNs would take a lot of time and space. The required measurements would also limit the modification of process parameters, e.g. the number of gateway devices. The raw values are already processed on the gateways and only the position information (but no RSS values) are available at the data concentrator PC. Hence, one set of measurement values cannot be analyzed with a different allocation set of RNs and gateways. For a parameterized computation using simulations of RSS distributions this is not an issue.

7.1. Infrastructure Components

The infrastructure which is used for the MineLoc tracking simulation uses a line of 196 reference nodes \( D = 1.5 \) m, which are placed at one side of the track with a displacement of \( d_d = 1.0 \) m. The displacement of the RN positions is necessary for an appropriate mounting of the nodes in real-life setups. Therefore, the smallest possible range between BN and RN is \( 1.0 \) m. The overall track length is \( 292.5 \) m, covering 196 reference nodes.

7.2. Indoor Fading Model

As shown in the application's environment in Fig. 1, there exists a dominating LOS component of the superimposed RSS and only a few NLOS conditions might occur, e.g. shadowing due to the human body. Thus, Rician fading is more suitable than Rayleigh fading to model the entire multipath fading channel [42].

The received signal strength which is measured by the RNs is modeled according to the log-distance model and the path loss results from experiments on a motion test track [43]. For the \( 1 \) m path loss intercept, a value of \( A_p = -60.45 \) dBm has been determined for the maximum probability combining of \( M = 8 \) redundant channels. For the receiver's sensitivity level, the according value of \( S_{min} = -94 \) dBm for 868 MHz is assumed.

The RSS values for the 42 RNs in the middle of the 292.5 \( m \) track are shown in Fig. 14 using different utilizations of the path loss model. The RSS resolution is given by the transmit cycle time of the BN and its speed. Here, the BN is assumed to move with a speed of \( v = 0.5 \) m/s along the track, periodically transmitting RF packets with \( f = 2 \) Hz. The resulting resolution is \( \Delta x = v/f = 0.25 \) m.

In Fig. 14(a), free-space propagation conditions \( (n_p = 2.0; \sigma = 0 \) dB \) are assumed. For the RNs' RSS values in Fig. 14(b), the empirical results for the combined RSS of \( M=8 \) redundant channels with \( n_p = 1.86 \) and \( \sigma = 2.07 \) dB are used. The resulting RSS values will be used for the following analysis of the systematic dWCL error.

7.3. Systematic dWCL Error Behavior

Before we analyze the impact of the flat fading behavior on dWCL, the influences of the (reduced) 4 Bit position resolution and the distributed computation will be analyzed. Therefore, the RSS-based range estimates are assumed to be error-free \( (\sigma = 0 \) dB \).

The influence of the reduced position resolution on the obtained accuracy of dWCL with \( s = 1 \) gateway is compared to centralized WCL using infrastructure setups with \( m = 31 \) RNs and \( m = 196 \) RNs. In Fig. 15, the resulting estimation error vector is analyzed for the middle part of the 292.5 \( m \) track. For a large RN-RN clearance, the systematic error behavior of WCL has the main influence on the dWCL estimation error.
With decreasing \( D \), the influence of the lower subnet position resolution on dWCL position estimation accuracy rises. For 196 RNs, the error which is introduced by the data compression is dominating the overall position estimation error. Nevertheless, the overall error is much lower than for a large RN-RN clearance.

In the following, the error degradation due to the distributed computations of dWCL will be analyzed. Again, the error-free RSS-based range estimates with \( n_p = 1.86 \) and \( \sigma = 0 \) dB are used to identify the systematic error behavior. In Fig. 16, the positioning accuracies of WCL and dWCL are compared for different values of the subnet weighting factor \( k \), indicating the influence of the BN's subnet positions \( p_i(x) \) on the final BN position \( P_i(x) \).

The absolute estimation error is plotted for the 42 RNs at the center of the track. The shown RN section is the same like for the simulated RSS plots in Fig. 14. For \( s = 14 \) gateways / subnets, the plot contains three subnet borders while RNs within the same subnet are colored the same. For small values of \( k \), the error of dWCL(\( s = 14 \)) is relatively high, especially for positions around the center and the edge of the subnets. For a relatively high dWCL weighting factor \( k = 50 \), the error for the center of the subnets is reduced significantly compared to \( k = 5 \). Nevertheless, for \( k = 50 \), there are large errors around the edge of the subnets.

The cause of this systematic error behavior is given by the dominating influence of the subnet with highest average RSS. A high average RSS translates into a high dWCL weight \( \nu_i \) for the centralized centroid position estimation. When \( k \) is small, the influence of the subnet with highest average RSS on the centroid computation of \( P_i(x) \) will be much lower. The adjacent subnets will pull the estimate to the edge of the corresponding subnet. Since the effect is larger for positions around the edge of the subnets, also the error will be larger for such positions. The optimum accuracy is achieved with \( k = 10 \), being a good trade-off between too strong weighting of the dominating subnet position and too less weighting in comparison to the weights of its adjacent subnets.

The optimum value of \( k \) depends on the infrastructure setup, given by the number of RNs \( m \), the RN-RN clearance \( D \) and the number of subnets / gateways \( s \). When \( m \) and \( D \) are set constant, the optimum value of \( k \) only depends on \( s \). The relation is shown in Fig. 17 for the RMSE of dWCL estimates. Again, the results are compared for different WCL weighting factors \( g \), where \( g = 2.4 \) is the optimum. For \( m = 196 \) RNs and \( D = 1.5m \), the best accuracy is achieved with \( s = 28 \) subnets and \( k = 10 \).

### 7.4. Tracking Results

To figure out the influence of the distributed position estimation on the accuracy of the longwall mining ILPS, two different utilizations are compared in the following: a centralized WCL computation, corresponding to \( s = 1 \) subnets / gateways and a distributed computation (dWCL) with \( s = 14 \) subnets. The RSS is modeled with the real-life path loss values according to Fig. 14.b (\( n_p = 1.86 / \sigma = 2.07 \) dB).

The position estimation error is given by the Euclidean distance \( e_x \) between the estimated position \( \hat{x} \) and the true position \( x \), which is the absolute difference of x-positions in the 1D case according to \( e_x = \| \hat{x} - x \|_2 = \| \hat{x} - x \| \). In Fig. 18, the errors of both configurations are compared for the partial track between the 42 RNs at the center of the longwall setup (RN 77 to RN 119).

For dWCL estimation with \( s = 14 \) subnets, the shown track part includes two complete subnets. For most of the position estimations at the center of a subnet, there are only small differences between
WCL and dWCL. At the subnet borders, the distributed computation shows the expected higher errors compared to the centralized WCL computation.

A comparison of the error for the complete 292.5 m longwall setup is given by the error cumulative distribution functions in Fig. 19 and detailed error statistics in Table 1. Both configurations with \( s = 1 \) subnets use a centralized position computation.

Fig. 17. Influence of the WCL weighting factor (g), the number of dWCL subnets (s) and the dWCL weighting factor (k) on the position estimation error (RMSE).

Fig. 18. Position estimation error for 1D tracking simulation of a mobile blind node (BN) using centralized (WCL) and distributed computation (dWCL) with \( s = 14 \) subnets. Extract shows results for BN movement from RN 77 to RN 119, passing three subnet borders.

Fig. 19. Cumulative position estimation error for 196 m linear track, comparing centralized computation (WCL) and distributed computation (dWCL) with \( s = 14 \) subnets and varying dWCL weighting factor k.

Thus, the error difference of WCL(\( s = 1 \)) and dWCL(\( s = 1 \)) indicates the influence of the smaller
Table 1. Comparison of position estimation error for centralized (WCL) and distributed (dWCL) weighted centroid localization (g=2.4) using m=196 RNs (D=1.5 m).

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>median</th>
<th>sigma</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>WCL (s=1)</td>
<td>0.41 m</td>
<td>0.35 m</td>
<td>0.32 m</td>
<td>0.52 m</td>
</tr>
<tr>
<td>dWCL (s=1)</td>
<td>0.47 m</td>
<td>0.50 m</td>
<td>0.37 m</td>
<td>0.60 m</td>
</tr>
<tr>
<td>dWCL (s=4)</td>
<td>0.58 m</td>
<td>0.49 m</td>
<td>0.56 m</td>
<td>0.80 m</td>
</tr>
<tr>
<td>k=5</td>
<td>0.51 m</td>
<td>0.50 m</td>
<td>0.46 m</td>
<td>0.69 m</td>
</tr>
<tr>
<td>dWCL (s=4)</td>
<td>0.51 m</td>
<td>0.50 m</td>
<td>0.47 m</td>
<td>0.69 m</td>
</tr>
<tr>
<td>k=10</td>
<td>0.51 m</td>
<td>0.50 m</td>
<td>0.47 m</td>
<td>0.69 m</td>
</tr>
<tr>
<td>dWCL (s=4)</td>
<td>0.61 m</td>
<td>0.55 m</td>
<td>0.48 m</td>
<td>0.81 m</td>
</tr>
<tr>
<td>k=5</td>
<td>0.50 m</td>
<td>0.46 m</td>
<td>0.40 m</td>
<td>0.65 m</td>
</tr>
<tr>
<td>dWCL (s=14)</td>
<td>0.54 m</td>
<td>0.50 m</td>
<td>0.47 m</td>
<td>0.71 m</td>
</tr>
</tbody>
</table>

When only one subnet is used, there is also no impact of the subnet weight \( v_i \) (and weighting factor \( k \)) on the position estimation error. For dWCL using \( s > 1 \), a factor of \( k = 10 \) for the subnet weighting is the optimum value. For smaller and larger values of \( k \), the dWCL with \( s = 4 \) subnets shows a better RMSE accuracy than dWCL using \( s = 14 \) subnets. Thus, for \( s = 4 \), the estimation accuracy is less sensitive to \( k \). Especially for \( k > 10 \), the error increases only slightly. Despite the smaller search space for the optimum value of \( k \), the better accuracy is achieved with \( s = 14 \) subnets. The influence of \( s \) on the RMSE is further investigated in Fig. 20 with the multivariate error analysis using a parameterization of \( s \) and \( k \). The general behavior of the error is the same like for the systematic error analysis in Fig. 17. Again, the best accuracy for dWCL is achieved with \( 5 \leq k \leq 15 \) and \( s \geq 14 \).

In Fig. 21, the RMSE and the achievable positioning coverage are shown for \( k = 10 \) and all possible segmentations.

8. Conclusions

With the initial considerations about communication resources and positioning coverage, all requirements are met by the hierarchical system using \( s = 14 \) subnets. The gained accuracy is slightly below the required accuracy for the longwall mining ILPS. With additional algorithmic measures, e.g. a plausibility filtering of range and / or position estimates, the desired accuracy with a RMSE below 0.5 m will be achieved [32].

The accuracy improvement for \( s = 28 \) compared to \( s = 14 \) is only marginal. Especially, it is not justifying the effort and hardware costs for the additional gateways. With \( s = 4 \) subnets, each CAN subnet contains 49 RNs. Thus, the maximum number of 32 CAN transceivers on a single CAN bus is exceeded and the configuration is not applicable. With \( s = 7 \) subnets, the number of 28 RNs in each CAN subnet meets the electrical load requirements.

Nevertheless, there exists a degradation of accuracy for \( s = 7 \) compared to \( s = 14 \).

With a centralized WCL computation, a specified CAN data rate of \( DR_{CAN} = 500 \text{ kBit/s} \) would be required, which limits the 1D system coverage to 43 m. With \( s = 14 \) subnets, a CAN data rate of \( DR_{CAN} = 50 \text{ kBit/s} \) is sufficient to transmit all necessary sensor information. The corresponding 1D system coverage is larger than 433 m. This corresponds to a coverage enhancement by factor 10, when a distributed computation with \( s = 14 \) subnets is used instead of a centralized one.

The distributed WCL implementation is essential to obtain the desired 1D positioning system coverage of 300 m. The coverage of the RN infrastructure is enhanced by a segmentation of the CAN data backbone and linking gateway devices. With 14 gateways and a position data compression by factor 14, it is possible to meet all criteria of the application of personnel tracking in the underground longwall mining environment. Furthermore, with the distributed concept, the system can easily be scaled to changing application’s needs.
References


