# Advanced methods for 3D magnetic localization in industrial process distributed data-logging with a sparse distance matrix

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**Abstract.** Wireless sensor networks/data-logging devices are increasingly applied for distributed measurement and acquiring additional contextual data. These have been applied in large scale indoor and outdoor systems with solutions based on RF, light based and ultra sound based systems. Data-loggers in liquid filled containers pose new challenges for localization because of the high reflectivity of containers and high attenuation due to the liquids obstructing communication between wireless nodes. Magnetic localization techniques have been used in many places including military research[14]. This approach was adapted for use in liquid filled containers. In this project, two prototypes, a laboratory and an industrial installation have been conceived and served for acquisition of experimental data for localization. In our paper, we exploit the sparsity met in the particular magnetic MEMS sensor swarm localization concept by introducing NLMR which is a simplified form of Sammon's mapping(NLM) and we combine it with different meta-heuristics & soft-computing techniques, e.g., gradient descent, Simulated Annealing and PSO. We compare this with Multilateration and conventional NLM localization technique. Our approach has improved the localization from a mean error of 20 cm in the first cut analysis for the industrial setup using conventional NLM down to 11 cm without and to 9 cm with apriori knowledge. Future improvements are to be expected from a thorough calibration of all system components.

**Keywords:** Magnetic sensor localization, Sammon's mapping, NLMR, Particle swarm optimization, PSO, Indoor localization.

## 1 Introduction

Sensors and Sensing systems are getting ubiquitous in industry and homes alike. Providing contextual information is essential and advantageous in industry and in ambient intelligence systems. Data-loggers have become prominent in such setups. Localization of such mobile sensors are traditionally done using RF, ultrasonic, IR and other methods. This spectrum of approaches is not suitable in our case, because of the high attenuation and reflections caused in liquid containers of industrial processes. Magnetic localization on the contrary can be a feasible method for localization in this situation.

Magnetic localization techniques have been in use for a long period of time from their introduction in 1962 [1]. They have been used in head tracking applications [3] in military [14], for silent localization of underwater sensors [9], in location and orientation tracking [8], in medical systems [13] [12].The approaches vary from using Internal(mostly in medical approaches) and External (Using artificially generated magnetic fields or earth magnetic field). In this project quasi-DC fields with artificially generated magnetic fields in coils is used. The idea behind such a localization approach for data-logging had its patent filed [21] on 18.05.2010. Similar idea has been used recently for data-logging in [20]. Interestingly an approach similar to this project is also being used in Indoor positioning systems [10] [11].

In the following section the particular project approach, providing the data for the localization algorithm experiments reported in this work, will be described in detail. Based on the data from measurement, localization algorithms are employed to estimate the coordinates of WSN nodes. Commonly, algorithms from, e.g., multi-dimensional-scaling (MDS), are employed. These basically are fine, but in their majority base on the assumption of a densely populated distance matrix and require substantial post-processing for the final coordinate determination. In the regarded research project, inter node communication is practically unavailable, so that the resulting distance matrix is sparse, i.e., having only anchor to sensor node non-zero entries. Thus, in this paper we investigate the recall extension of Sammon's non-linear mapping (NLMR) for localization purposes and compare it with multilateration based on data acquired in the industrial target environment. Also, we enhance NLMR with different soft computing techniques and show that we can get more than competitive results, than original Sammon's mapping(NLM) with much less computational effort.

## 2 The Localization System Setup

In our localization concept and implementation triaxial Anisotropic Magnetoresistive (AMR) sensors complementing the data-loggers which will be deployed in the liquid containers. A magnetic coils system has been mounted on the container hull producing quasi-DC magnetic fields controlled by a central control unit synchronized to the sensors clock. This is used to produce voltage values in the sensors, which can be converted to distances. These distances can be used to compute the location of the sensor node.

### Sensor Node

In the project, artificially generated magnetic fields are sensed by a triaxial Anisotropic Magneto-resistive(AMR) sensor. AMR sensor makes use of a magnetoresistive effect to detect magnetic fields. In the project, AMR sensor type AFF755B from Sensitec Gmbh was used to design a proprietary 3D sensor. The Fig. 2 shows a PCB AMR sensor. There is currently a MEMS prototype which will be used in future experiments.

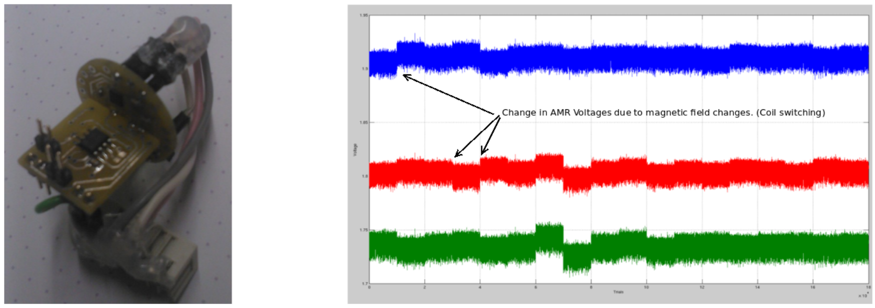


**Fig. 1.** 3D AMR sensor node (left), noisy raw data obtained from 3D AMR node in a scaled down ISE lab setup (right)

### Magnetic Field Generation

There are different types of coils that could be used for magnetic field generation. In this project, circular coils of container specific diameters are used to generate the fields. The coils should be positioned in such a way that there are at least 4 magnetic fields observed by the sensor at any point in the cylinder. Generally localization is done in such a way the distance between the coil and the sensor is much greater that the radius of the coil.

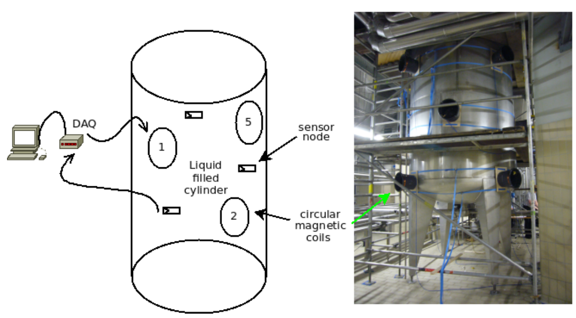


**Fig. 2.** Sketch of the measurement system with sensor and coils (left), photo of industrial container with coils (right)

Magnetic fields are not simultaneously produced from all the coils. The magnetic field are generated one coil at a time. Each coil is switched-on in both directions. Ternary switching allows a differential and energy-aware measurement, eliminating static magnetic offsets and reducing the flipping of AMR sensors to a minimum. In the experiments a DAQ board(DT9816) was used to control the coils and in data acquisition as shown in the Fig. 2. In the final planned setup the control circuitry is different for the coil switching and reading from AMR. The clock synchronization errors can be resolved by using synchronization methods described in [19].

**Distance Calculation**

Three distances are obtained for each activation of the coil. These voltages are converted into distances using the formulae given below. The angle between the node and the sensor is not considered since it is an unknown. However there are techniques which could be used as mentioned in [18].

$$d = \left( \left( \frac{\frac{1}{2} \times \mu_0 \times n \times R^2 \times I}{B_M} \right) - R^2 \right)^{\frac{1}{2}} \tag{1}$$

where,

$$Bm = \frac{V_M}{S \times V_S \times G}, V_M = \frac{V_i^p - V_i^n}{2}, i = \{x, y, z\}$$

where S is the sensitivity, $V_S$ is sensor voltage, G is the gain of the amplifier, n is the number of windings, R denotes the radius of the coil and $\mu_0 = 4 \times \pi \times 1e^{-7}$.

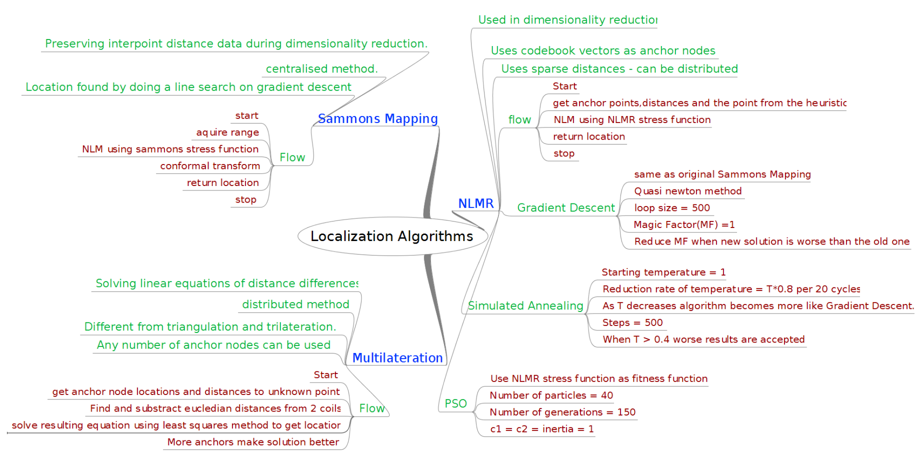


**Fig. 3.** Survey of localization algorithms and parameter settings.

## 3 Localization

### MDS mapping

MDS mapping is a popular technique used in localization. There are many types of MDS mapping, we are interested in the non linear Sammon's mapping(NLM). In NLM localization is done based on reducing the cost function E(m)

$$E = \frac{1}{\sum_{i=1}^{N-1} \sum_{j=i+1} N d_{ij}^*} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{(d_{ij}^* - d_{ij})^2}{d_{ij}^*} \tag{2}$$

where N is number of nodes, $d_{ij}^*$ is Euclidean distance between $X_i$ and $X_j$ in Higher dimension and $d_{ij}$ is Euclidean distance between $Y_i$ and $Y_j$ in lower dimension. In the localization problem there is no dimensionality reduction. The main disadvantage of this method in our scenario is that we do not have inter sensor distances. A modification to Sammon's mapping that limits the involved number of distances seems promising [5].

### NLMR

Sammons recall or NLMR was described in [5] for dimensionality reduction. This technique is a simplification of Sammons mapping(NLM) where inter point distances are ignored and a set of code-book vectors(previously mapped points) are used to find the positions of all points. This is much less resource consuming as compared to Sammons mapping (NLM)[5]. Here we have a cost function E(m) described by,

$$E_i(m) = \frac{1}{c} \sum_{j=1}^{K} \frac{(d_{Xij} - d_{Yij}(m))^2}{d_{Xij}} \tag{3}$$

where,

$$d_{Xij} = \sqrt{\sum_{q=1}^{m} (v_{iq}^r - v_{jq}^t)^2}, c = \sum_{j=1}^{K} d_{Xij}$$

$d_{Xij}$ is the distance between recall and training data in high dimensional space and K is the number of code book vectors.The distances in the new space are found using gradient descent technique

**Gradient Descent :** In the Gradient Descent approach we make use of the NLMR cost function and the following equations.

$$y_{iq}(m+1) = y_{iq}(m) - MF \times \Delta y_{iq}(m) \tag{4}$$

with,

$$\Delta y_{iq}(m) = \frac{(\frac{\partial E_i(m)}{\partial y_{iq}(m)})}{(\frac{\partial E_i^2(m)}{\partial y_{iq}(m)^2})}, 0 < MF \leq 1 \tag{5}$$

Where $y_{iq}(m+1)$ is the new position, MF is the magic factor which reduces with time, $y_{iq}(m)$ is the current position and E(m) is the cost function at the current position.

**Modification :** The specialty of NLMR approach is that it matches perfectly with our requirements. We do not obtain an inter-point distance between the nodes. We have a set of mapped positions (coils).We have to make some changes to the original algorithm to make it work for localization.

In our case we do not require a dimensionality reduction. So the known locations(magnetic coils) will act as the trained data set. We do not have any location for the unknown value, however we have the distance information from the known locations which can be directly given to the algorithm.

Unlike Sammon's mapping we do not have to do a reverse mapping(conformal transform) after we get our output.

After making these changes, We can make use of any soft-computing technique to generate the values to be given to the Sammon's recall function. In our approach we tried Gradient descent, simulated annealing and PSO.

**NLMR - Gradient descent :** The gradient descent approach makes use of Quasi- Newton method similar to the method described in Eqn. 4, [5]. We make use of Magic factor with a starting point of 1 and reduce it every time the new fitness is not as good as the old fitness. Only better solutions are accepted in this approach.

**NLMR - Simulated Annealing :** We use the basic simulated annealing where we start with a high temperature which is reduced over the number of cycles (here 20) and reduce the chances of getting a worse solution as the temperature decreases. an energy component is not explicitly used in this approach. The algorithm runs for 500 iterations to get the best solutions. The number of iterations required was found heuristically.

**NLMR - Particle swarm optimization :** Standard particle swarm optimization described in [4] is used with $C_1 = C_2 = 1$ and the algorithm has no inertia. Having no inertia helped in faster convergence of the algorithm. 40 particles were used with 150 generations found the best results in the experiments.The standard PSO was unable to converge to a solution using Sammon's mapping and required special approaches to reach convergence [15]. However, in the modified NLMR method the standard PSO is able to converge easily.

**Multilateration :** Multilateration is used in wireless sensor networks and a standard technique for efficient and effective localization. It serves as a reference in our work. Traditionally the time difference of arrival of the signal is used in multilateration technique, We use the distances obtained with our magnetic localization system. In our approach we make use of the linear least squares method (Moore-Penrose pseudo-inverse) to get the best fit solution.

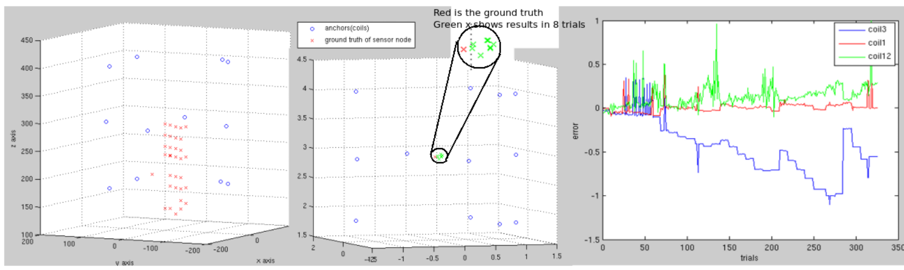


**Fig. 4.** Plot showing the ground truth and anchor (coils) locations(left), Results for 8 trials on one ground truth location (middle), Variations between expected distances and acquired distances for 325 experiments(right)

**Coil Selection :** In the previous works of this project coil selection was used by taking a heuristic of the closest distances (effectively closest coils (anchors)) available. However in our data analysis we found that erroneous distances detected by the sensor was also present in closer coils. In our analysis we compared the distances from the sensor and the distances calculated from the ground truth value. In Fig. 3, three coils with their distance errors are plotted for all our data. The peaks correspond to distance errors due to angle (which is not honored in our current formula for distance calculation). In Fig. 3, we can see the original positions where the sensors were placed. Even though coil 12 was furthest from any of the data points while coil 3 was close to most of them coil 3 has a higher error as compared to coil 12. The reason behind this maybe due to an unfortunate angle with respect to the data points. Here, we remove 4 coils depending on such a study (coils 3,10,11,12) and observe the improvement in results. More research on coil selection will be done in our future work.

## 4 Results

The data acquisition based on the container of Fig. 2 (right), was confined to a cubic volume in the container of $350cm \times 350cm \times 250cm$. The acquired data was first-cut analyzed in prior project work, employing the conventional NLM localization method. These previous results serve as the baseline to comparatatively evaluate the suggested new methods. In the tables below we use Localization

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Error (LE) which is the distance between the ground truth and obtained values. All experimental results used parameters mentioned in Fig. 3. In addition to

| trials | pos | trials/pos | coils | coil dia. | windings | V-Sensor | I-coils |
|---|---|---|---|---|---|---|---|
| 325 | 40 | 2 to 20 | 12 | 0.25 m | 230 | 3.7V | 3A |

**Table 1.** Parameters used in the industrial setup

| **All Coils** | **NLMR-GD** | **NLMR-SA** | **NLMR-PSO** | **Multilateration** |
|---|---|---|---|---|
| LE$\mu$ | 0.17951 | 0.17914 | **0.11429** | 0.16702 |
| LE$\sigma$ | 0.13097 | 0.12557 | **0.06580** | 0.15194 |
| Max LE | 0.76031 | **0.62029** | 0.69258 | 1.31961 |
| Min LE | 0.02230 | 0.01720 | **0.00911** | 0.01302 |
| $\mu$ X | -0.09350 | -0.09780 | **-0.00121** | -0.05915 |
| $\mu$ Y | 0.08262 | 0.08639 | **0.01846** | -0.02365 |
| $\mu$ Z | 0.02610 | 0.02201 | 0.02336 | **-0.00190** |
| $\sigma$ X | 0.14338 | 0.13490 | **0.06336** | 0.12351 |
| $\sigma$ Y | 0.08881 | 0.08591 | **0.07171** | 0.11815 |
| $\sigma$ Z | 0.06942 | **0.06904** | 0.08571 | 0.13306 |
| Max err X | 0.67247 | 0.55810 | 0.50856 | **0.48092** |
| Max err Y | 0.58066 | 0.55335 | **0.50618** | 0.60638 |
| Max err Z | **0.20882** | 0.21477 | 0.30020 | 1.15277 |
| Min err X | 0.00017 | **0.00001** | 0.00018 | 0.00043 |
| Min err Y | 0.00140 | 0.00060 | 0.00065 | **0.00020** |
| Min err Z | 0.00026 | 0.00026 | 0.00021 | **0.00011** |
| **Sel. Coils** | **NLMR-GD** | **NLMR-SA** | **NLMR-PSO** | **Multilateration** |
| LE $\mu$ | 0.10106 | **0.09345** | 0.09534 | 0.13912 |
| LE $\sigma$ | **0.05822** | 0.05861 | 0.06129 | 0.11206 |
| Max LE | 0.69430 | **0.68370** | 0.70647 | 0.80797 |
| Min LE | 0.01774 | 0.01126 | 0.01239 | **0.00573** |
| $\mu$ X | **-0.00238** | 0.01458 | 0.00813 | -0.03728 |
| $\mu$ Y | **0.00126** | 0.00150 | 0.00686 | -0.03760 |
| $\mu$ Z | **0.00323** | 0.02655 | -0.00776 | 0.03375 |
| $\sigma$ X | 0.04970 | **0.04145** | 0.04564 | 0.07312 |
| $\sigma$ Y | 0.06513 | 0.06770 | **0.06290** | 0.09209 |
| $\sigma$ Z | 0.08290 | **0.07033** | 0.08144 | 0.11892 |
| Max err X | 0.19471 | **0.13390** | 0.17319 | 0.19803 |
| Max err Y | 0.52350 | 0.53103 | 0.49736 | **0.49735** |
| Max err Z | **0.50800** | 0.57788 | 0.58183 | 0.78424 |
| Min err X | 0.00043 | **0.00010** | 0.00043 | 0.00012 |
| Min err Y | **0.00003** | 0.00007 | 0.00065 | **0.00003** |
| Min err Z | 0.00033 | 0.00021 | **0.00009** | 0.00018 |

**Table 2.** Results making use of all available anchors (coils) (top), results using anchors (coils) selected by apriori knowledge.(1,2,4,5,6,7,8,9) (bottom), all values are in meters

the *stale* database from the industrial environment, we extracted fresh data from the ISE lab setup, which has just six smaller scaled coils in an orthogonal arrangement of $150cm \times 150cm \times 150cm$. Raw data in Fig. 2 was obtained here. In a first step, 56 different locations with just one trial each were sampled in a single Z-plane and the data was subject to multilateration and the suggested methods. The results given in Tab. 4 in comparison to Multilateration confirm the viability of our approach. The ISE lab demonstrator is reshaped to cylindrical shape and campaigns with different sensor heads including MEMS and wireless sensor will follow-up.

| trials | pos | trials/pos | coils | coil dia. | windings | V-Sensor | I-coils |
|---|---|---|---|---|---|---|---|
| 56 | 56 | 1 | 6 | 0.13 m | 100 | 5V | 5A |

**Table 3.** Parameters used in the ISE lab experimental setup

| | NLMR-GD | NLMR-SA | NLMR-PSO | Multilateration |
|---|---|---|---|---|
| LE $\mu$ | 0.07169 | **0.07137** | 0.08715 | 0.12526 |
| LE $\sigma$ | **0.03312** | 0.03429 | 0.03428 | 0.07147 |
| $\mu$ X | -0.05512 | 0.05434 | **0.05112** | 0.10509 |
| $\mu$ Y | 0.03315 | **0.03307** | 0.03383 | -0.05274 |
| $\mu$ Z | 0.00532 | -0.00639 | -0.00744 | **-0.00212** |
| $\sigma$ X | **0.02857** | 0.02953 | 0.03727 | 0.07489 |
| $\sigma$ Y | 0.02062 | **0.02057** | 0.02612 | 0.03253 |
| $\sigma$ Z | 0.02881 | 0.02978 | 0.05372 | **0.01735** |

**Table 4.** First-cut results from ISE lab orthogonal demonstrator

## 5 Conclusion

In our work, we have presented an adaptation of NLMR, a simplified Sammon's mapping for dimensionality reduction and used it for localization with a sparse distance matrix, e.g., for liquid filled containers or general indoor localization. This was applied to industrial data available as benchmark and obtained comparable results to Multilateration. The results were also better than those achieved by conventional NLM in first-cut analysis with the same data. We also presented simulated annealing and particle swarm optimization to reduce the NLMR cost function and these methods provide better results than the commonly used gradient descent method [2] [5]. The standard NLMR PSO even provides results for all coils selected comparable to results of the other methods when coils giving unreliable information are removed.

## 6 Acknowledgments

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