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PARTICLE SWARM OPTIMIZATION ALGORITHM BASED LOW COST MAGNETOMETER CALIBRATION

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ABSTRACT: Inertial Navigation Systems (INS) consist of accelerometers, gyroscopes and a microprocessor provide inertial digital data from which position and orientation is obtained by integrating the specific forces and rotation rates. In addition to the accelerometers and gyroscopes, magnetometers can be used to derive the absolute user heading based on Earth's magnetic field. Unfortunately, the measurements of the magnetic field obtained with low cost sensors are corrupted by several errors including manufacturing defects and external electro-magnetic fields. Consequently, proper calibration of the magnetometer is required to achieve high accuracy heading measurements. In this paper, a Particle Swarm Optimization (PSO) based calibration algorithm is presented to estimate the values of the bias and scale factor of low cost magnetometer. The main advantage of this technique is the use of the artificial intelligence which does not need any error modeling or awareness of the nonlinearity. The estimated bias and scale factor errors from the proposed algorithm improve the heading accuracy and the results are also statistically significant. Also, it can help in the development of the Pedestrian Navigation Devices (PNDs) when combined with the INS and GPS/Wi-Fi especially in the indoor environments.

1. INTRODUCTION

In the recent years, inertial sensors are becoming more popular for navigation in cluttered indoor environments that are challenging for Global Navigation Satellite Systems (GNSS). Inertial Navigation Systems (INS), consist of accelerometers, gyroscopes, and a microprocessor, provide position and orientation by integrating the specific forces and rotation rates. However, any errors in the inertial sensor data are accumulated rapidly with time even with high accuracy sensors. Consequently, regular updates are necessary to provide a drift free position and orientation solution. For updating the position, GNSS signals are utilized, and for heading updates magnetometers may be employed.

For navigation as well as in control applications, heading information of mobile bodies is a paramount importance. The magnetometers based on Anisotropic Magneto-Resistive (AMR) technology depend upon the Earth's Magnetic Field (EMF) from which the heading information can be derived. The ubiquitous nature of EMF makes these sensors available in airplanes, vehicles, ships, and they are now being explored in hand-held devices. Cameras using optical flow, gyroscopes, and odometry (wheel encoder) may also be adopted in addition to a magnetometer to get the heading information (Kwon et al., 2006). In order to improve the robustness of the heading solution an optimal fusion of these sensors is justifiable. This again depends upon the cost, accuracy, and type of application at hand.

In most of the early research, the calibration proceeds in the heading domain (Guo et al., 2005). Also in (Crassidis et al., 2005; Gebre and Elkaim, 1995), the calibration algorithm is applied in the magnetic field domain. The advantage of applying the calibration algorithm in the magnetic field domain is convincing, as we do not have to depend on the heading of the sensor prior to calibration. For a given region, the Earth's total magnetic field is constant and its value can be obtained from the International Geomagnetic Reference Field (IGRF) model. This becomes a basis for developing a mathematical model for sensor calibration (Siddharth et al., 2011).

Different reasons are listed to use Particle Swarm Optimization (PSO) technique over statistical based approaches such as Extended Kalman Filter (EKF) and Particle Filter (PF) where they may fail to converge for the appropriate calibration parameters. These failures may be seen in its inherent nature of operation (Siddharth et al., 2005):

- No *a priori* knowledge of initial sates.
- Inaccurate knowledge of noise statistics (Process Noise/state Covariance).
- Matrix implementation, especially, inversion operation which may lead increased computation time and singularity.

Artificial Intelligence (AI) based algorithms are considered as practical tools for nonlinear optimization problems (Reeves, 1993) where such algorithms do not require that the objective function be differentiable and continuous. PSO is one of the modern heuristic algorithms (Kennedy and Eberhart, 1995) and can be applied to nonlinear optimization problems. It has gained wide recognition due to its ability to provide solutions efficiently, requiring only minimal implementation effort. In the paper we introduce the PSO procedure into calibration process to estimate the bias and scale factor. Three bias and three scale factor terms corresponding to each axis of the tri-axial magnetometer are estimated, which constitutes the six elements of the state vector. The mathematical description and notations used for describing all the states is described in section 2.

Section 2 discusses the mathematical background for calibration. In section 3, a brief discussion for particle swarm optimization technique is provided. Section 4 describes the proposed estimator algorithm adopted in magnetometer calibration. The calibration test results with magnetometer data are presented and discussed in section 4. The paper ends with a conclusion in section 5.

2. A CONSTRAINED CALIBRATION APPROACH

Based on the Earth magnetic field, the formulation can be stated by the following mathematical equation:

$$B = AH + b + \varepsilon \tag{1}$$

Also we can write Equation 1 in the form:

$$\mathrm{H} = \mathrm{A}^{-1}(\mathrm{B} - \mathrm{b} - \varepsilon) \tag{2}$$

where, $\boldsymbol{H}$ = the estimated EMF,
$\boldsymbol{B}$ = the measured magnetic field, magnetometer readings, $B = [B_x \quad B_y \quad B_z]^T$,
A = the diagonal matrix of the scale factor where $A = diag(SF)$.
SF = Scale factor vector $[a_x,\ a_y,\ a_z]^T$
b = bias vector $[b_x,\ b_y,\ b_z]^T$
ε = the noise

[3] To simplify the mathematical formulation we can ignore the white noise which is not part of the model used for calibration parameters in the estimation process, in this case, Equation 2 can be rewritten as:

$$\mathrm{H} = \mathrm{A}^{-1}(\mathrm{B} - \mathrm{b}) \tag{3}$$

The bias and scale factor are estimated subject to:

$$\mathrm{H}_\mathrm{m}^2 - \|\mathrm{H}\|^2 = \mathrm{H}_\mathrm{m}^2 - \mathrm{H}^\mathrm{T}\mathrm{H} = 0 \tag{4}$$

Where H_m is the magnitude of Earth's magnetic field in a given geographical location obtained from the IGRF model. [2, 4] The IGRF parameters are revised every five years by a group called the International Association Geomagnetism and Aeronomy (IAGA). The user is required to input the latitude, longitude and height of the place where the Earth's magnetic field intensity is sought. The 11th generation IGRF accepts the year in between 1900-2020. The accuracy of the estimated Earth's magnetic field is claimed to be 1nT (0.01 milliGauss) by the IAGA.

3. PARTICLE SWARM OPTIMIZATION

Bird flocks, fish schools, and animal herds are examples of natural systems where an organized behaviour produced impressive, collision-free, and synchronized moves. In such systems, the behaviour of each group member is based on simple inherent responses. Although swarm intelligence is still in its infancy compared to other paradigms in artificial intelligence, nevertheless, it is an attractive new research field.

PSO is a population based stochastic optimization technique, developed by Eberhart and Kennedy in 1995 (Kennedy, et al., 2001). They claimed that searching for food source is similar to finding a solution for a common research goal (Hernane et al., 2008). In comparison with other AI optimization techniques, the power of PSO lies in its simplicity in implementation. The performance of different optimization techniques in industry and computing are evaluated and compared which indicates that PSO performed better than other algorithms in terms of success rate, solution quality, and convergence speed (Elbeltagi et al., 2008).

The PSO technique employs a set of feasible solutions called a 'swarm of particles' that are populated in the search space with initial random positions and velocities and at any particular instant, each particle has its own position and velocity. During each iteration, each particle is updated by following two "best" values. The particle best, P_{best} or P_i^k, is the best position of the particle itself. Another "best" value is the global best, g_{best} or P_g^k, which is the best value obtained so far by any particle in the population. All particles have the influence of these two bests in its search space (Åkesson et al., 2008).

For a random particle swarm of N particles and search space dimension of D, define the i[th] position and change in position of the particle as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $\Delta x_i = (\Delta x_{i1}, \Delta x_{i2}, \ldots, \Delta x_{iD})$ respectively. The PSO algorithm can be performed by the following equation:

$$\Delta X_i^{k+1} = w.\Delta X_i^k + c_1 r_{i1}^k \left(P_i^k - X_i^k\right) + c_2 r_{i2}^k \left(P_g^k - X_i^k\right) \tag{5}$$

$$X_i^{k+1} = X_i^k + \Delta X_i^{k+1} \tag{6}$$

Where $i = 1, 2, \ldots, N$ with N the population size,

c_1 and c_2 = acceleration coefficients, usually $c_1 = c_2 = 2$,

r_{i1} and r_{i2} = random numbers uniformly distributed within the range [0, 1].

w = inertial weight factor, and the bigger the value of w, the wider is the search range.

ΔH = magnitude error of total magnetic field

Equation 5 is used to determine the i[th] particle's new velocity, change in position, at each iteration, while Equation 6 provides the new position of the i[th] particle by adding the increment in the position to its current position. The initial weight value is fixed to 1 all the time where c_1 and c_2 values are 2.

$$\Delta H = \mathrm{H}_\mathrm{m}^2 - \mathrm{H}^\mathrm{T}\mathrm{H} \tag{7}$$

$$Fit\_Value = \sqrt{\sum(\Delta H)^2} \tag{8}$$

The performance of each particle is measured according to a fitness function, which is problem-dependent. In optimization problems, the fitness function is usually identical with the objective function under consideration. Equation 7 shows the used fitness function which it is the difference (error) between the estimated total magnetic field and the reference value. The reference value is 170 *mGauss* in the case of 2-D calibration and 560 *mGauss* for the 3-D calibration case. The fitness value is computed in Equation 8 as the square root of the summation of the squared error.

The algorithm re-evaluates all particles' locations after each iteration and takes the new best values. To find the optimum value, a recurring searching process is done until the maximum iteration number is reached or the minimum error condition is achieved. The PSO can be shown as in Figure 1:

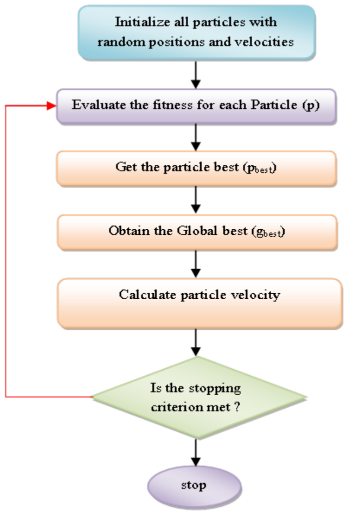

Fig. 1: The basic PSO algorithm

4. METHODOLOGY

4.1 PSO Based Calibration Approach

The proposed algorithm is used to estimate the bias (b) and scale factor (SF) by minimizing the difference between the measured magnetic field and the true magnetic field derived from IGRF model. It exploits the fact that the incorrect heading estimates due to the magnetometer biases, scale factors and declination angles have a relationship with the true heading. The PSO algorithm is used to estimate the required parameters for calibration.

As mentioned in section 2 and by substituting Equation 2 in Equation 3, the difference between the true total Earth magnetic field and the measured one can be written as:

$$(A^{-1}(B-b))^T\big(A^{-1}(B-b)\big) = H_m^2 \tag{9}$$

$$(A^{-1}(B-b))^T\big(A^{-1}(B-b)\big) - H_m^2 = 0$$

$$(B-b)^T(A^{-1})^T A^{-1}(B-b) - H_m^2 = 0$$

$$(B-b)^T\lambda(B-b) - H_m^2 = 0$$

$$B^T\lambda B + uB - K = 0 \tag{10}$$

Where $\lambda = (A^{-1})^T A^{-1}$

$u = -2b^T\lambda$

$K = b^T\lambda b - H_m^2$

The value scale matrix A is evaluated as the diagonal matrix of the scale factor where $A = diag(SF)$.
The main objective of proposed algorithm is to estimate the values of the scale factor and bias respectively;

$SF = [a_x,\ a_y,\ a_z]^T$, and $b = [b_x,\ b_y,\ b_z]^T$.

The different values of the bias and scale factor are estimated by using Equation 5.

4.2 The Auto-Selection Algorithm

For the conventional magnetometer based calibration approaches, the whole measurement is employed and involved in the estimation process. Such techniques don't have the ability to minimize, or at least decrease, the required time for the calibration process. Certain real time navigation applications demand fast and accurate calibration. It is complicated to have flexible algorithm that can provide accurate calibration parameters in suitable time. The auto-selection algorithm is used to decide which part of the raw data will be used while in the calibration mode. The proposed technique is searching for the maximum change in the magnetic field for each axis and gets the interval in between. The algorithm receives the overall raw measurements and returns the start and end indices of the nominated interval as shown in Figure 2.

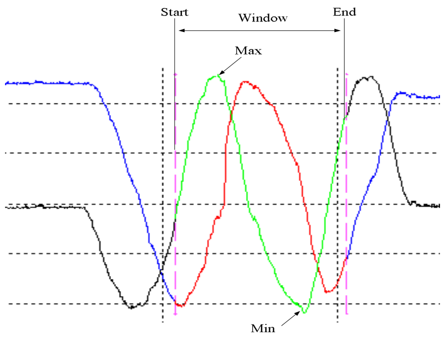

Fig. 2: The auto-selection algorithm

4.3 Stopping Criterion

The PSO based calibration parameters estimation technique is based on an iterative process. To estimate the bias and SF, an iterative process is conducted during the proposed algorithm for the required parameters. In order to increase the convergence speed of the algorithm, the trust in the random ranges assigned to the parameters of interest may be set wisely. This may be done by knowing these parameters roughly from the auto-selection algorithm described earlier. Over the iterations, the bias and SF values converge to the best values. The purpose of our method is to decide when the calibration process is done. The stop criterion takes three different levels:

- Maximum number of iterations
- Hit a minimum error
- Hit the tolerant of the change in the bias and SF values

5. RESULTS

In a free-environment, the norm of the magnetometer vector measurement should be equal to the magnitude of the Earth's magnetic field which can be extracted from a specific geomagnetic model. To assess the new calibration technique, field tests were conducted at the University of Calgary campus including static, walking, indoors and outdoors cases. All measurements are raw sensor readings from the Honeywell 3-axis magnetometer (HMC5843). For the 2D calibration, the magnetometer was rotated 360◦ in the horizontal plane and then the heading was computed using the estimated SF and b. In all tests, the algorithm successfully converges to a good estimate of the SF and b values and showed improvement in terms of heading accuracy after the calibration.

5.1 Basic PSO Results

The first group of results is for the basic PSO algorithm in indoor environment where the whole magnetometers measurements are passed to the calibration algorithm. The test is conducted in multi-sensor lab at the University of Calgary. The test is a two 360 degrees turn about z-axis using a rotation table (shown in Figure 3). The PSO for indoor scenario did fairly well in estimating the bias and scale factors.

Fig. 3: Rotation table

Figures 4-7 illustrate the calibration results where PSO represents the solutions of Particle Swarm Optimization. Figure 4 shows the raw magnetic field in the *x* and *y* directions. The total horizontal raw and calibrated magnetic fields are shown in Figure 5.

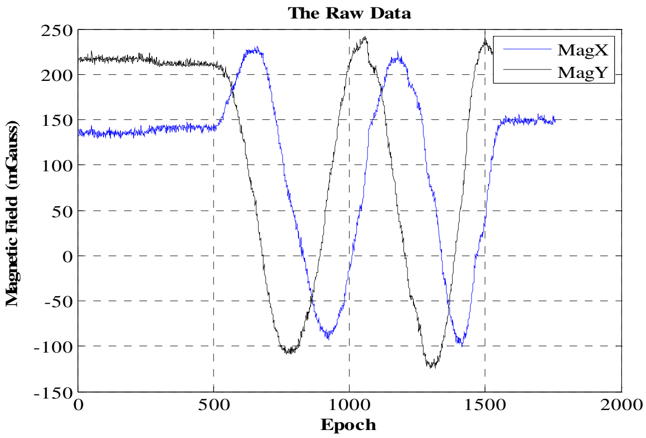

Fig. 4: Raw magnetic field measurements

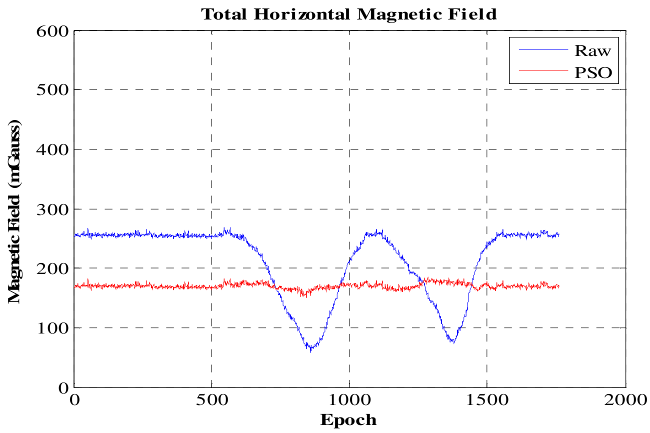

Fig. 5: Horizontal raw and PSO calibrated magnetic field

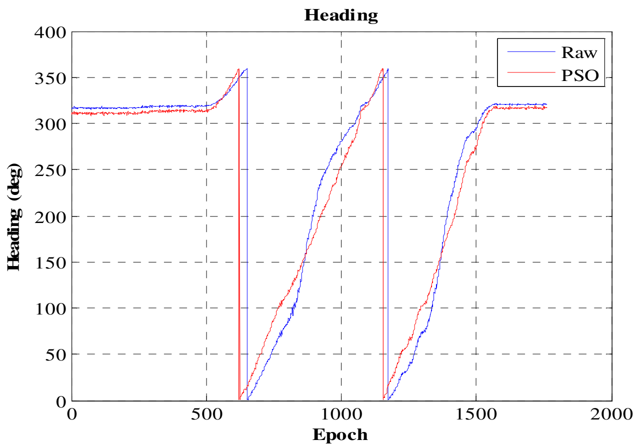

Fig. 6: Raw heading and PSO corrected

Figure 6 shows two 360 degrees turns about z-axis on a rotation-table. The corresponding raw heading and PSO corrected are depicted in the figure. Clearly, the PSO based algorithm shows the ability to estimate the necessary parameters to provide corrected, calibrated, and adjusted results as shown in Figure 7.

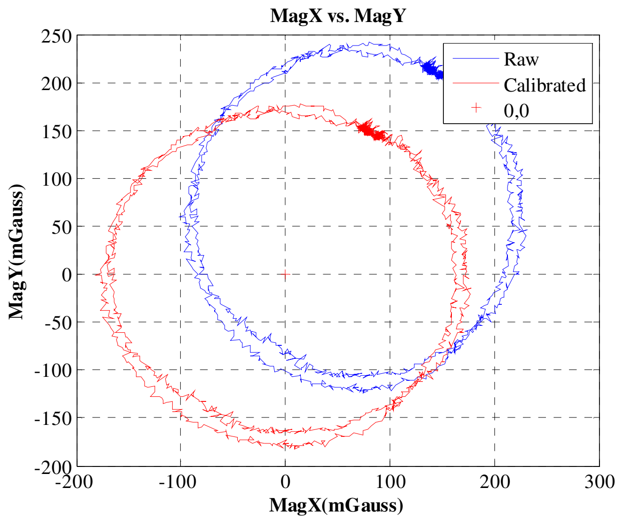

Fig. 7: 2D calibration for adjusted magnetic field

5.2 Applying Auto-Selection Algorithm

The auto-selection algorithm is applied to accelerate the calibration process and reduce the time needed to complete the whole operation. Only a specific, window of the measured data is applied to the PSO algorithm. The results show that the PSO continues to performance robustly while the total time for the calibration process is reduced. As the PSO is working with the input measurements as a whole part, so the number of samples is a very important factor which affects the overall performance. The results from the PSO with the whole data and part of the data are shown in Figures 8-11. The term “Sel&PSO” refers to the results with applying the auto-selection algorithm. While the results from PSO only and Sel&PSO showed similar accuracies, the Sel&PSO considerably reduced the time complexity in estimating the parameters of interest. The selected part from the data in both x and y directions is shown in Figure 10 where this part from the data is selected to cover the maximum peak to peak variation in the data.

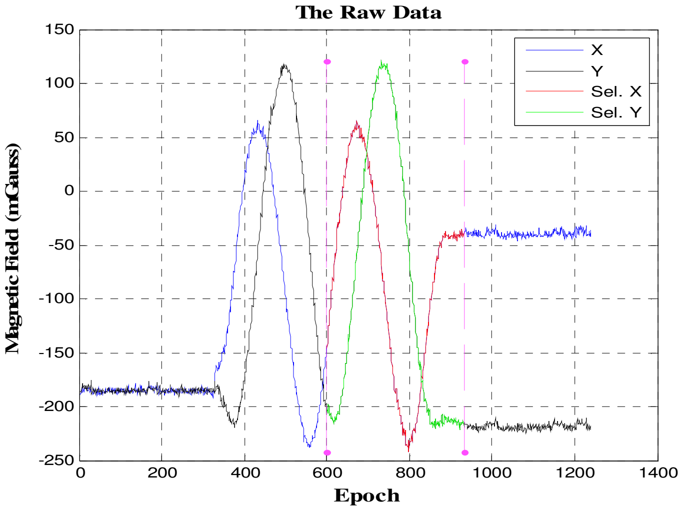

Fig. 8: The selected part of the measurements

Figure 11 shows the total magnetic field with the raw PSO and the PSO with part of the data. Although less information is applied to the PSO algorithm, the accuracy of the results hasn't been affected.

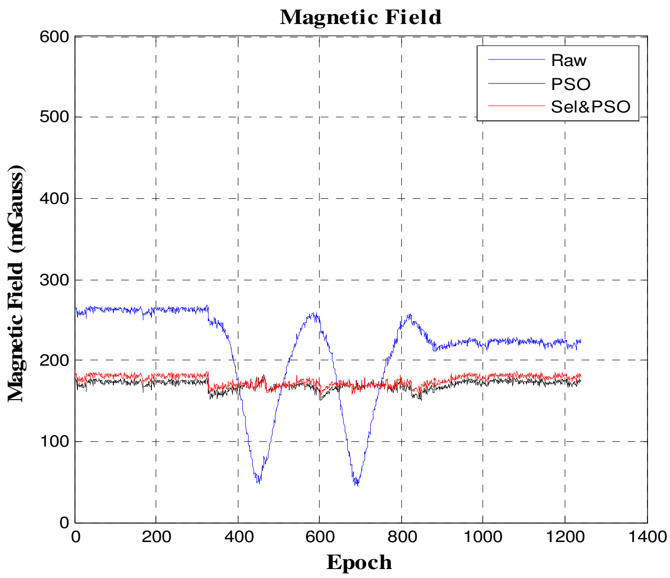

Fig. 9: Total horizontal raw and PSO calibrated magnetic field

As revealed from Figures 10 and 11, the proposed algorithm succeeded to give good performance.

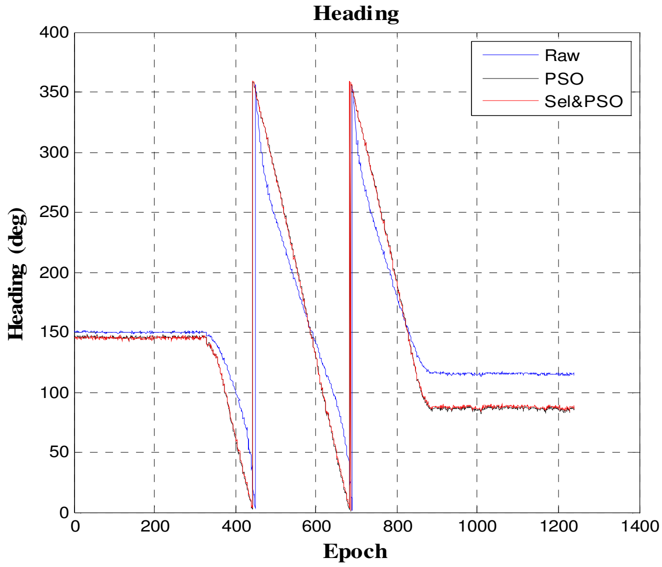

Fig. 10: Raw heading and PSO corrected

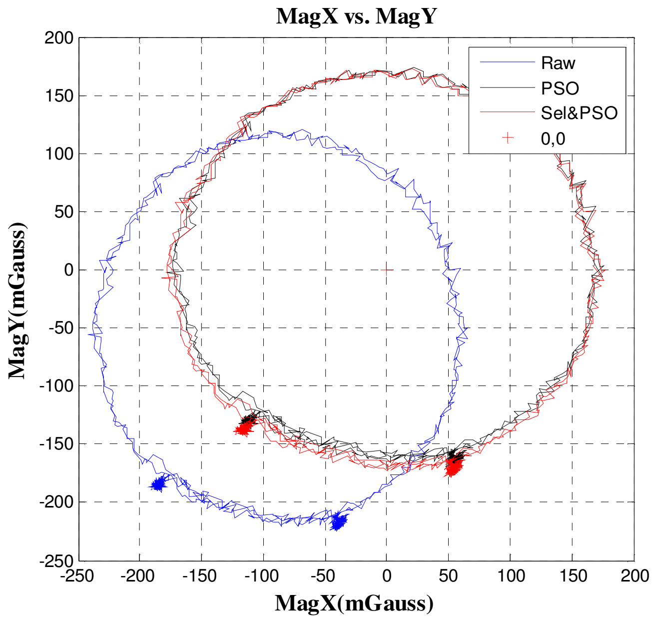

Fig. 11: 2D calibration for adjusted magnetic field.

Different tests are conducted in different situations where Table 1 summarizes the results.

Tab. 1: calibration parameters for both x and y axis

Data	*Test #*	*# of Samples*	*SF*	*bias (mGauss)*
All	1	1240	[0.873 0.998]	[-87.279 -54.190]
Part		297	[0.866 0.973]	[-87.419 -50.008]
All	2	1560	[0.601 0.655]	[33.490 42.887]
Part		401	[0.598 0.649]	[32.674 42.193]
All	3	1760	[0.925 1.018]	[66.016 61.332]
Part		487	[0.913 1.050]	[63.461 58.556]
All	4	1493	[2.498 2.720]	[36.912 42.229]
Part		489	[2.535 2.773]	[50.207 51.725]
All	5	2360	[0.791 0.872]	[19.483 42.121]
Part		538	[0.793 0.869]	[19.986 43.142]

5.3 Applying Stop-Criterion Technique

Stop criterion technique aims to indicate that the calibration process is achieved efficiently. Once the bias and scale factor values are converged, the algorithm stops and produces the final estimated values of the parameters. This method reduces the total number of iterations improving the potential for real time applications. Results are depicted in Figures 12-15 where the term “PSO&Stop” refers to the modified PSO algorithm with the stop-criterion technique.

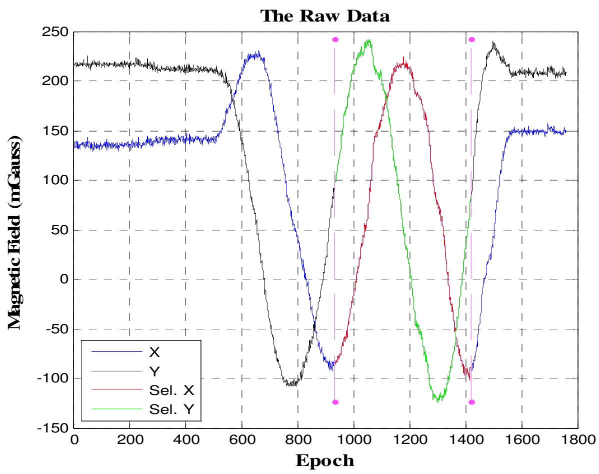

Fig. 12: The selected part of the measurements

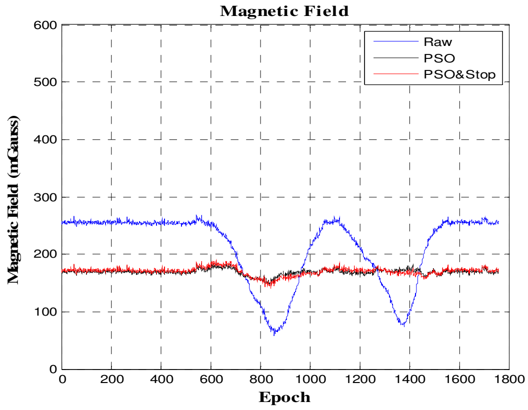

Fig. 13: Total horizontal raw and PSO calibrated magnetic field

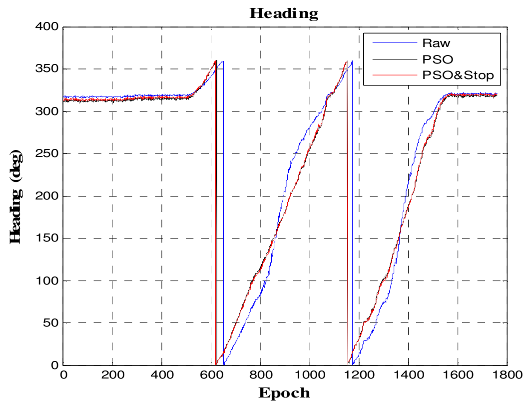

Fig. 14: Raw heading and PSO corrected

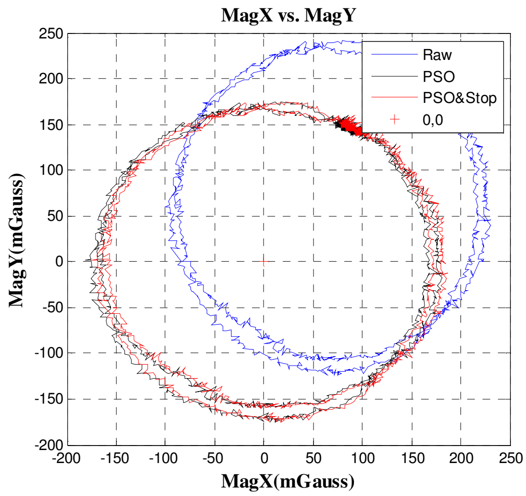

Fig. 15: 2D calibration for adjusted magnetic field.

Tab.2: Calibration parameters for the PSO with and without the stop criterion.

Stop Criterion	Test #	# of Iter.	SF	bias
x	1	353	[0.858 0.982]	[-85.615 -50.381]
√		99	[0.863 1.027]	[-86.025 -46.695]
x	2	500	[0.597 0.649]	[32.659 42.003]
√		90	[0.602 0.629]	[29.960 43.227]
x	3	360	[0.913 1.050]	[63.563 58.489]
√		104	[0.911 1.049]	[62.955 58.503]
x	4	301	[2.534 2.773]	[50.356 51.822]
√		94	[2.535 2.773]	[50.162 51.590]
x	5	286	[0.787 0.856]	[18.750 40.415]
√		81	[0.775 0.859]	[16.295 47.760]

Table 2 manifests that the number of iterations required for convergence is decreased. Applying the stop criterion holds the accuracy of the estimated bias and scale factor while the number of iterations in most cases decreased to be less than 1/3 the required number without the proposed technique.

6. CONCLUSION

In this paper, a PSO based calibration algorithm is presented to estimate the values of the bias and scale factor applicable to low cost magnetometer. The main advantage of this technique is the use of the artificial intelligence which does not need any error modeling or awareness of the nonlinearity. The estimated bias and scale factors from the proposed algorithm improved the heading accuracies and the results are also statistically significant. This technique would help in the pedestrian navigation to decrease the heading error of the user. Also, it can help in the development of the Pedestrian Navigation Devices (PNDs) when combined with the INS and the available RF signals, especially in the indoors environments. Clearly, the proposed algorithm beside the auto-selection and stop-criterion techniques decreased the required time for the calibration process extending the opportunity to apply the proposed algorithm in real-time navigation applications.

7. ACKNOWLEDGEMENTS

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