Calibration and testing techniques for nanosatellite attitude system development in magnetic environment

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Abstract

The development of nanosatellites, which are generally defined by its weight ranging between 1kg-10kg, have grown considerably in the academia sector. The most popular form factor for spacecrafts in this category is the CubeSat form factor, as it opens up lower-cost launch opportunities and growing availability of commercial-off-the-shelf solutions for the spacecraft subsystems. For many nanosatellites orbiting in Low Earth Orbit, magnetic environment is an important aspect in its design consideration. This applies to both the platform engineering and mission design, as it influences the attitude system design as well as the design of the relevant scientific instruments.

This thesis work contributes in the development of technology and techniques that can help in managing the influence of magnetic environment in spacecraft design, in particular the solution for magnetometers calibration and the detection of spacecraft residual magnetic dipole moment. The magnetometer calibration focuses on the implementation of rotational correction factor, which, in the more conventional techniques, is typically assumed to be in a certain condition. The detection of spacecraft residual magnetic dipole moment focuses on the early development of a machine-vision-assisted test bed that aims to reduce the mechanical and electrical complexity of the more common spacecraft automated magnetic test bed.

Several missions, where the spacecraft has been developed and built in Aalto university, has been launched. From the perspective of practical performance of in-orbit spacecraft operation, this thesis work will also discuss the challenges and lessons learned from the operation of Aalto-1 attitude system. This thesis contribution is focused on the attitude analysis and sensors calibration of the Aalto-1 in-orbit operation.
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This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.


Author’s contributions

Publication I: “Particle Swarm Optimization With Rotation Axis Fitting for Magnetometer Calibration”

The thesis author is the main author of the paper. The research idea is motivated by the nanosatellite project needs and developed by the first author. The author carried out the algorithm development, set up the simulation environment, and performed data processing for simulation results and ground tests. The first author also wrote the paper text and acted as corresponding author. Other authors helped the project with system requirements, satellite physical implementation, and comments.

Publication II: “Particle swarm optimization for magnetometer calibration with rotation axis fitting using in-orbit data”

The thesis author is the main author of the paper. The original research idea is developed by the first author and stemmed from previous work. The author carried out the algorithm development, set up the simulation environment, and performed data processing and analysis for simulations and in-orbit data. The first author was also responsible for writing of the paper text and acted as corresponding author. Other authors helped the project with satellite operations, data acquisitions, and comments.

Publication III: “Aalto-1, multi-payload CubeSat: In-orbit results and lessons learned”

This paper is an extensive effort of large group, describing and summarizing the results and lessons learned of entire satellite mission. The author of this thesis acted in this project as an attitude system specialist who
supported the mission with attitude and maneuver analysis. Specifically, the thesis author contributed with satellite development, calibration of magnetometer and gyroscope data, as well as the overall ADCS analysis of Aalto-1 satellite during the mission. The author also wrote the text related to the attitude system performance analysis.

Publication IV: “Radiation monitor RADMON aboard Aalto-1 CubeSat: First results”

This paper describes scientific results of Aalto-1 satellite mission RADMON instrument. The author was responsible for the attitude analysis of the spacecraft during the payload measurement period. The key attitude analysis was to determine the rate at which RADMON scanned the sky relative to its sensor integration time, as full attitude information is not available at real time to complement RADMON data. This information was cross-checked between the spacecraft gyroscope and magnetometer data in order to derive the rotation rate along with its precession and nutation characteristics.

Publication V: “Design of magnetorquer based attitude control subsystem for FORESAIL-1 satellite”

This paper describes the design and development of magnetorquer coils as attitude actuator in Foresail-1 satellite. The author of this thesis assisted with the development of coil manufacturing process and provided simulation data of attitude control under different scenarios in order to verify the coils performance. Besides the development process described in the paper, the author of this thesis is also responsible for verifying the magnetic moment of the produced coils using magnetic test bed developed in this thesis work.
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Abbreviations

**ADCS** Attitude Determination and Control System

**COTS** Commercial-off-the-shelf

**DCM** Direction cosine matrix

**DUT** Device-under-test

**EKF** Extended Kalman Filter

**EM** Engineering model

**EPB** Electrostatic Plasma Brake

**ESA** European Space Agency

**FMI** Finnish Meteorological Institute

**IGRF** International Geomagnetic Reference Field

**LEO** Low Earth Orbit

**MDM** Magnetic dipole model

**MOPSO** Multi-Objective Particle Swarm Optimization

**PSO** Particle Swarm Optimization

**RADMON** Radiation Monitor

**RMM** Residual magnetic moment

**SVD** Singular value decomposition
Symbols (Latin letters)

\( b \) magnetic field in magnetometer calibration
\( b_s \) magnetic field at measurement point \( s \) in magnetic dipole estimation
\( F_i,F_g \) local and global fitness value, respectively
\( gbest \) swarm global best position
\( K_m \) magnetometer distortion calibration
\( K_{Qm} \) magnetometer rotational calibration
\( K_{Rm} \) magnetometer skewing calibration
\( k_m \) magnetometer offset calibration
\( m_d \) magnetic dipole moment of dipole \( d \)
\( \vec{n}_i,l \) rotation normal vector from magnetic field measurement locus
\( \text{off}_g \) gyroscope offset error model
\( \text{off}_m \) magnetometer offset model
\( pbest_i \) swarm’s \( i \) particle local best position
\( p_s \) position of dipole \( d \)
\( p_s \) position of measurement point \( s \) in magnetic dipole estimation
\( \text{rand}() \) random function
\( S_m \) magnetometer distortion error model
\( S_g \) gyroscope distortion error model
Symbols (Greek letters)

$\eta_m$ magnetometer noise

$\eta_{\text{ARW}}$ gyroscope angular random walk

$\eta_{\text{RRW}}$ gyroscope rate random walk

$\omega$ angular velocity

$\dot{\omega}_l$ reference rotation normal vector
Symbols (Others)

**lower case + bold:** vector

**UPPER case + bold:** matrix

□: mean value

■: calibrated value

□: measured/uncalibrated value

‖: error value

|□| scalar absolute value/vector magnitude
1. Introduction

Nanosatellites, typically defined by its mass in the range of 1 kg–10 kg, have seen a lot of development in the last two decades. A lot of these developments are largely contributed by the popularity of the CubeSat standard, which has opened up lower-cost launch opportunities as well as faster spacecraft development cycle with the growing options of commercial-off-the-shelf (COTS) solutions[7, 24]. Lower costs and faster development cycle makes spacecraft projects more accessible for many applications, including scientific missions initiated by the academia. The down-scaled size and cost of the spacecraft means that it will not fully replace full-scale scientific (or commercial) capabilities of larger spacecraft. However, it could fill different scientific goals and technology demonstration which would otherwise be too cost-prohibitive on a larger spacecraft[30].

In order to carry out its mission, the spacecraft, even a small one, should provide several reliable functions to the payload. One of the important function in a spacecraft, which will be the focus of this thesis, is the attitude determination and control of the spacecraft. The spacecraft subsystem responsible for this function is aptly called the attitude determination and control system (ADCS); it is responsible for ensuring that the knowledge and control over the spacecraft orientation (as it rotates freely around its center of mass) can fulfill the mission requirements. To accurately determine the spacecraft orientation, a combination of attitude sensors such as magnetometers, gyroscopes, sun sensors, and star trackers are typically installed in the spacecraft. With this spacecraft attitude information, attitude actuators such as magnetorquers, reaction wheels, and thrusters then can be used to manipulate the spacecraft attitude to fulfill different conditions as required by the mission.[47, 41]

While solutions for attitude sensors are typically not a prohibiting element in nanosatellites development, attitude actuators are relatively more limiting. This is due to the fact that most attitude sensors are passive instruments (which means low power requirement) and come in very small form factor—except star trackers, which require more elaborate optics and thus larger dimension. Attitude actuators, however, are ac-
tive instruments by nature (except some passive control methods, which will sacrifice some controllability), which means it requires more power to manipulate the physical orientation of the spacecraft; it also requires more mass and volume as attitude control in space largely depends on the principle of momentum exchange. Due to these reasons, the majority of nanosatellites that require active, precise attitude control are equipped with magnetorquers and reaction wheels.[50] magnetorquers in particular is needed for off-loading momentum build-up in the system, as reaction wheels operate on internal momentum exchange, while thrusters add much more complexity in the spacecraft mass and volume management as it requires fuel storage.[41] This correlates with the fact that the majority of nanosatellites are operating in Low Earth Orbit (LEO), as magnetorquers need to interact with strong enough ambient magnetic field in order to generate sufficient control torque.[13, 50] This thesis will focus on ADCS instruments that interact with magnetic environment, i.e. magnetometers and magnetorquers.

Magnetic environment itself is an important aspect in spacecraft design, both from the spacecraft engineering and the mission design perspective. Spacecraft material selections and electrical systems can influence the local magnetic field; this will affect the design of attitude system as well as scientific instruments that interact with the magnetic environment. Because of this, on-board sensor (i.e. magnetometers) calibration is important to ensure that the system performance fulfills the mission requirement. This thesis work will put heavy emphasis on the technology and techniques that can help in managing the influence of magnetic environment in spacecraft design, in particular the solution for calibrating magnetometers and the characterization of spacecraft residual magnetic moment (RMM).

For magnetometer calibration, a new approach is developed for solving rotational ambiguity by fitting the measurement data with reference rotation axis information. This rotation axis fitting approach is combined with the more conventional scalar checking method[14, 44, 52] in a particle swarm optimization (PSO) algorithm in order to estimate the associated calibration parameters. The calibration algorithm performance will be verified and analyzed using simulated, ground test, and real in-orbit data. The in-orbit data is acquired from Aalto-1 and ESTCube-1 satellite missions. This approach will show the technical performance of the calibration algorithm using the reference simulated data, as well as the practicality of the algorithm implementation in a real in-orbit scenarios.

For the characterization of spacecraft RMM, this thesis introduces the development of a machine-vision assisted test bed for spacecraft residual magnetic field measurement in Aalto University. An initial look into the test bed performance, i.e. the final accuracy of estimated RMM, will be evaluated using permanent magnets with known magnetic moments. The same test bed will also be used to investigate the RMM of the Electrostatic
Plasma Brake (EPB) module of Foresail-1 satellite, as well as to verify the magnetic moment produced by a magnetorquer coil from the same satellite. Additionally, this thesis will highlight some of the challenges in the operation and ADCS analysis of Aalto-1 satellite.

This thesis will be structured as follows: chapter 2 will describe the basic theories and equations that govern the main magnetic interactions relevant to the thesis work; chapter 3 will describe the algorithm used in the magnetometer calibration; chapter 4 will focus on the results of the calibration algorithm tests and verification, both from simulations, ground tests, and in-orbit flight data; chapter 5 will describe the development of an automated test-bed for the estimation of spacecraft residual magnetic dipole moment including some preliminary test results; chapter 6 will depart from the spacecraft design perspective of the previous chapters and will discuss the challenges and lessons learned from the hands-on perspective of in-orbit spacecraft ADCS operation and analysis; and chapter 7 summarizes the key findings from each chapter.
2. Spacecraft Magnetic Environment

This chapter summarizes the basic theory and mathematical model of the key magnetic interactions related to this thesis work, which includes magnetic torque and dipole moment as well as the model for related sensors.

2.1 Magnetic Torque

Interaction between ambient magnetic field and the spacecraft magnetic moment will generate torque governed by the equation

\[ \tau_m = m \times b, \]

(2.1)

where \( \tau_m \) is the magnetic torque, \( b \) is the ambient magnetic field, and \( m \) is the spacecraft magnetic dipole moment. This magnetic dipole moment could originate from the spacecraft structures, materials, and the electronics current loop, or it could be generated by magnetorquer coils as active attitude actuator. A more in-depth process in the design and development of magnetorquers for spacecraft attitude control is discussed in Publication V.

2.2 Sensor Mathematical Models

This thesis work focuses mainly on two spacecraft attitude sensors: magnetometer and gyroscopes. Magnetometer directly measures the ambient magnetic field and is main target of the calibration algorithm developed in this work, while gyroscopes represents the reference information needed in the magnetometer calibration process.

2.2.1 Magnetometer Model

The simplified mathematical model that describes the relationship between the measured magnetic field vector \( \hat{b} \) and the reference ambient magnetic
Spacecraft Magnetic Environment

The measured magnetic field $b$ is:

$$
\hat{b} = S_m (b + \text{off}_m + \eta_m),
$$

(2.2a)

where $3 \times 3$ matrix $S_m$ and $3 \times 1$ vector $\text{off}_m$ are the compounded calibration parameters from the combination of individual magnetometer error sources, with more details discussed in Publication I, p. 1010. $\eta_m$ is the magnetometer measurement noise. In magnetometer calibration, the calibration parameters need to transform the measured magnetic field $\hat{b}$ into the corrected magnetic field $\hat{b}$, flipping eq. (2.2a) into

$$
\hat{b} = K_m \hat{b} - k_m.
$$

(2.2b)

The measurement noise $\eta_m$ is assumed as zero-mean Gaussian random process, while $K_m = S_m^{-1}$ and $k_m = \text{off}_m$ are the calibration parameters that need to be optimized by the calibration algorithm.$^{[35, 25, 28]}

2.2.2 Gyroscope Model

A three-axis gyroscopes is used as the source for reference axis information in the rotation axis fitting method. Gyroscopes measurement can be described as

$$
\dot{\omega} = S_g \omega + \text{off}_g + \eta_{\text{ARW}},
$$

(2.3a)

where $\dot{\omega}$ is the measured angular rate, $S_g$ is the gyroscopes total scale factor, $\omega$ is the true angular rate, $\text{off}_g$ is the angular rate bias with a drifting rate

$$
\text{off}_g = \eta_{\text{RRW}},
$$

(2.3b)

which is also known as the rate random walk (RRW), while $\eta_{\text{ARW}}$ is the measurement noise or angular random walk (ARW). Both $\eta_{\text{ARW}}$ and $\eta_{\text{RRW}}$ are assumed as zero-mean white noise. The variance of these noise sources can be determined, for example, using Allan Variance.$^{[12, 34, 51]}

2.3 Magnetic Dipole Modeling

Spacecraft structure and electronics might generate its own magnetic moment, which could be modeled as different sources.$^{[19]}$. This thesis work focuses on the hard magnetic sources (stable magnetic properties under ambient magnetic field) as the main source of RMM. For small spacecrafts orbiting in LEO, disturbance torque generated by the RMM is often the dominant disturbance torque.$^{[45]}$. This disturbance torque effectively reduces the coil’s available power to control spacecraft attitude, as portion of it is used to negate the disturbance torque. Discussion on how available power, among other variables, affects the control performance is also
demonstrated using simulations in Publication V. Fig. 2.1 demonstrates how spacecraft RMM affect the performance of spacecraft detumbling maneuver.

Figure 2.1. Plot of spacecraft rotation speed with active detumbling under the influence of different RMM magnitude.

In order to minimize this magnetic disturbance torque, proper design on material and component selections as well as electrical design should be implemented. The next approach is to model the spacecraft as a set of magnetic dipole that will represent the spacecraft RMM, which can be compensated in different ways depending on the specific objectives of the RMM management, e.g. minimizing disturbance torque and/or remanent magnetic field. This magnetic model of the spacecraft is called the multiple magnetic dipole model (MDM).

In MDM, the magnetic field generated by the spacecraft is represented by a finite numbers of magnetic moment dipoles. This relationship is defined by the equation\(^{20, 45}\)

\[
b_s(p_s, p_d, m_d) = \frac{\mu_0}{4\pi} \sum_{d=1}^{n_d} \left( \frac{3 (p_s - p_d) (p_s - p_d)^\top}{|p_s - p_d|^5} - \frac{1_3}{|p_s - p_d|^3} \right) m_d, \tag{2.4}
\]

where \(s = [1, n_s] \in \mathbb{Z}\) and \(d = [1, n_d] \in \mathbb{Z}\) are the indexes of measurement points and magnetic dipoles, respectively; \(b_s\) is the theoretical magnetic field at measurement point \(s\); \(\mu_0\) is the environment magnetic permeability; \(p_s\) and \(p_d\) are the coordinates of \(s\)-th measurement points and \(d\)-th magnetic dipole, respectively; \(m_d\) is the magnetic moment of the \(d\)-th dipole; and \(1_3\) is a \(3 \times 3\) identity matrix.
3. Development of PSO with Rotation Correction Factor

PSO was first introduced as nonlinear function optimization algorithm in [8, 21]. It has been implemented in very wide range of field; [9] and [31] documented various fields of study where PSO has been implemented. This thesis summarizes the implementation of PSO in magnetometer calibration for spacecrafts by combining scalar checking method with rotation axis fitting method with the following structure: Section 3.1 describes the core PSO algorithm, Section 3.2 describes the definition of the optimization objectives, and Section 3.3 expands the details of the PSO architecture and parameters selections. Section 3.2 and Section 3.3 in particular highlight the differences between the PSO implementation used in Publication I and Publication II.

3.1 Basic PSO Algorithm

In [48, 49, 1], PSO is used for solving the parameters estimation problem in magnetometer calibration because of its better capability in finding global solution without a good initial estimate. Most of the PSO variations proposed were designed for optimizing the scalar checking objective only, while the rotational ambiguity is resolved by simplifying the calibration parameters in $K_m$ from eq. (2.2b) into a diagonal or triangular matrix, requiring assumptions that at least one sensor axis is perfectly aligned to the reference frame in order to reduce the number of unknown parameters from 12 to 9 or 6 parameters. Regardless of the search space and objective definition, the core of PSO algorithm contains the following iteration steps:\textsuperscript{(4, 9)}:

1. Swarm initialization: initialize $n_p$ numbers of particles (the \textit{swarm size}) with random initial ‘position’ $p_i(k = 0)$ and random initial ‘velocity’ $v_i(k = 0)$ in an abstract $n^c$-dimensional space (the \textit{swarm dimension}), or, written in mathematical notation:

$$p_i(k) = [p_{i1}(k), p_{i2}(k), \ldots, p_{in^c}(k)] \equiv [p_{ij}]_{j=1}^{n^c}(k),$$

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Development of PSO with Rotation Correction Factor

\[
v_i(k) = [v_{i1}(k), v_{i2}(k), \ldots, v_{in^c}(k)] \equiv [v_{ij}|j=1...n^c(k)],
\]

where the subscript \(i\) is the particle index \((i = [1, n_p] \in \mathbb{Z})\), subscript \(j\) is the particle component index \((j = [1, n^c] \in \mathbb{Z})\), and \(k\) is the iteration index. The number of unknown parameters \(n_c\) corresponds to the swarm dimension \(n^c\), i.e. \(n^c = n_c\).

2. Swarm positions update: the velocity and position of each particle are updated with the basic formula\(^4, 5\)

\[
v_{ij}(k+1) = w_{ij}(k) + \text{rand}(0, 1) c_1 (p_{best_{ij}}(k) - p_{ij}(k)) + \text{rand}(0, 1) c_2 (g_{best_{j}}(k) - p_{ij}(k)),
\]

\[
p_{ij}(k+1) = p_{ij}(k) + v_{ij}(k+1),
\]

where \(\text{rand}(0, 1)\) is a random number in the range of \([0...1] \in \mathbb{R}\), \(w\) is the inertia weight parameter, \(c_1\) is the cognitive rate parameter, and \(c_2\) is the social rate parameter.

3. Best solution evaluation: \(p_{best_i}\) represents the position with the best fitness value that each particle \(i\) have encountered, while \(g_{best}\) represents the best position among all the swarm particles. On every iteration, \(p_{best_i}\) is replaced by the new particle position if the fitness value is better than the last one. Since the magnetometer calibration is formulized as a minimization problems, the evaluation can be mathematically written as

\[
p_{best}(k) = \arg \min_{p_i} f(p_i(1...k)),
\]

while the global best position is obtained from the local best position with the best fitness among all particles, or, in mathematical notation

\[
g_{best}(k) = \arg \min_{p_{best_i}} f(p_{best_i}(k)),
\]

where \(f()\) is the fitness function which returns the fitness value

\[
F_i = f(p_i), \quad \text{for } i = 1...n_p,
\]

with the notation for the fitness value of the local and global best positions \((F_i\text{ and } F_g, \text{ respectively})\) are written as

\[
F_i \equiv f(p_{best_i}), \quad F_g \equiv f(g_{best}).
\]

4. Iteration evaluation: the algorithm will determine whether the swarm has reached its goal by checking several predefined conditions. In this thesis work, the iteration ends when a set maximum number of iteration \(k_{max}\) has been reached.

This core PSO algorithm is summarized in Fig. 3.1.
3.2 Optimization Objectives

In Publication I, the goal of the calibration algorithm is to optimize the value of $K_m$ and $k_m$ (distortion matrix and bias vector, respectively) from eq. (2.2b), where $K_m$ is defined as a full $3 \times 3$ matrix, i.e. the matrix $K_m$ translates as 9 parameters to be optimized, with total 12 parameters by including the bias vector $k_m$. The estimated calibration parameters themselves are contained in the PSO solution (for each particle) with the mathematical structure

$$p_i = \begin{bmatrix} K_{m11,i} & K_{m12,i} & K_{m13,i} \\ K_{m21,i} & K_{m22,i} & K_{m23,i} \\ K_{m31,i} & K_{m32,i} & K_{m33,i} \end{bmatrix}, \quad k_m = \begin{bmatrix} k_{m1,i} \\ k_{m2,i} \\ k_{m3,i} \end{bmatrix}.$$  

where

$$K_{m,i} = \begin{bmatrix} K_{m11,i} & K_{m12,i} & K_{m13,i} \\ K_{m21,i} & K_{m22,i} & K_{m23,i} \\ K_{m31,i} & K_{m32,i} & K_{m33,i} \end{bmatrix}, \quad k_m = \begin{bmatrix} k_{m1,i} \\ k_{m2,i} \\ k_{m3,i} \end{bmatrix}.$$  

All these 12 parameters are then optimized with multi-objective PSO (MOPSO) to combine the two objectives (scalar checking and rotation axis fitting).

In Publication II, the matrix $K_m$ is decomposed with QR decomposition into orthogonal and upper triangular matrix. The upper triangular matrix $K_{Rm}$ represents distortion of the magnetometer measurement locus with the $z$-axis perfectly aligned with the reference $z$ direction (e.g. the spacecraft body frame), while the orthogonal matrix $K_{Qm}$ represents the rotational error of the magnetometer measurement locus. Thus, $K_{Qm}$ is a
direction cosine matrix (DCM) describing the angular displacement of the magnetometer z-axis from the reference.

Implementation of scalar checking method is limited for solving triangular matrix (scaling and skewing error) and bias vector, which have been demonstrated with various algorithms\cite{15, 17, 38}, including using PSO algorithm\cite{1}. In Publication II, PSO is implemented to directly solve the upper triangular matrix $K_{rm}$ and bias vector $k_m$ for every particle $i$, which are defined as

\[
K_{rm,i} = \begin{bmatrix}
K_{rm1,i} & K_{rm2,i} & K_{rm3,i} \\
0 & K_{rm4,i} & K_{rm5,i} \\
0 & 0 & K_{rm6,i}
\end{bmatrix},
\]

while the orthogonal matrix $K_{qm}$ is not directly solved with PSO, because from the 9 elements in an orthogonal matrix, only 3 parameters are independent. To translate the actual physical rotation properties of $K_{qm}$ into the PSO search space, $K_{qm}$ is represented in Euler rotation sequence form.

In a Euler rotation sequence form, the PSO search parameters can be converted into the rotation matrix $K_{qm}$ with the straightforward equation

\[
K_{qm,i} = \begin{bmatrix}
c_1c_3 - c_2s_1s_3 & -c_1s_3 - c_2c_3s_1 & s_1s_2 \\
c_3s_1 + c_1c_2s_3 & c_1c_2c_3 - s_1s_3 & -c_1s_2 \\
s_2s_3 & c_3s_2 & c_2
\end{bmatrix},
\]

where $s$ and $c$ denotes \textit{sine} and \textit{cosine}, and the subset 1, 2, 3 denotes the Euler sequence rotation angle defined by $K_{qm1,i}$, $K_{qm2,i}$, $K_{qm3,i}$ respectively, e.g. $c_1 = \cos(K_{qm1,i})$, $s_3 = \sin(K_{qm3,i})$, and so on. Other conversion formulas under different notations are available in literature\cite{47}.

In Publication II, the two objectives are optimized in separate PSO runs. Thus, from the components of $K_{rm}$, $K_{qm}$, and $k_m$, we define two separate PSO search spaces:

\[
p_{i,R} = [K_{rm1,i}, \ldots, K_{rm6,i}, k_{m1,i}, k_{m2,i}, k_{m3,i}]
\]

\[
p_{i,Q} = [K_{qm1,i}, \ldots, K_{qm3,i}].
\]

Then, the final calibration matrix is calculated back from QR decomposition with

\[
K_{m,i} \equiv K_{qm,i}K_{rm,i}.
\]

With these definition of the search space, we then define the PSO objectives:
3.2.1 Scalar Checking

Scalar checking objective minimizes the difference between the calibrated magnetic field vector magnitude $|\hat{b}|$ with the known reference magnetic field magnitude $|b|$[47, pp. 328–330]. We can translate this mathematically as the fitness function

$$F_{1,i} = \sum_{s=1}^{n_s} \left[ |b_s| - |\hat{b}_{i,s}| \right]^2, \quad (3.9a)$$

or, by substituting eq. (2.2a) into eq. (3.9a):

$$F_{1,i} = \sum_{s=1}^{n_s} \left[ |b_s| - |K_{m,i} \hat{b}_s - k_{m,i}| \right]^2, \quad (3.9b)$$

where $i = [1, n_p] \in \mathbb{Z}$ and $s = [1, n_s] \in \mathbb{Z}$ are the index for swarm particles and measurement data, respectively. Note that while in Publication I, the scalar checking objective directly optimizes $K_m$, in Publication II, the scalar checking objective only optimizes the upper triangular matrix part $K_{Rm}$ in eq. (3.8), while the orthogonal rotation matrix part $K_{Qm}$ is optimized separately by the rotation axis fitting objective.

3.2.2 Rotation Axis Fitting with Fixed Measurement Locus Plane

The principle of rotation axis fitting objective is to estimate a rotation plane from the magnetometer measurement locus and fit it to a known reference rotation plane. Publication I and Publication II use different approaches in the rotation plane estimation and fitting methods. In Publication I, a set of magnetic field measurements from the magnetometer is grouped as such that the measurement locus can be separated into at least two loci $l$, where each locus forms a circle (not necessarily a complete circle) on a plane with different normal directions. This means that for each locus, the spacecraft ideally needs to rotate on a fixed single axis. The goal of the calibration is then to rotate these circular loci as such that the locus plane normal $\hat{n}_{i,l}$ (the plane containing a circle of measurement locus $l$ after calibrated by particle $i$) is aligned with its respective known rotation axis $\omega_l$. Mathematically, the fitness function for this rotation axis fitting can be defined as:

$$F_{2,i} = \sum_{l=1}^{n_l} \left[ 1 - (\hat{n}_{i,l} \cdot (-\omega_l)) \right]^2 \quad (3.10)$$

where the subscripts $i$ and $l$ are the index for the swarm particle and the individual measurement locus that lies on a single plane, respectively. The unit vector $\hat{n}_{i,l}$ is the normal direction of the rotation plane estimated from the calibrated magnetometer measurement locus, and the unit vector $\omega_l$ is the reference rotation axis that corresponds to the measurement locus.
Development of PSO with Rotation Correction Factor

This reference information can be derived from gyroscope data, direct observation (e.g., in preflight test), or estimated from vector sensors such as star trackers or other image processing technique\cite{18,2,10}. Note that the direction of $\dot{\omega}_l$ is inverted with a minus sign because the direction of magnetometer rotation is the opposite of the measurement locus sequence. In summary, the second fitness function $F_{2,i}$ represents the sum of angular difference between $\hat{n}_{i,l}$ and $\dot{\omega}_l$ for $i = 1 \ldots n_p$ and $l = 1 \ldots n_l$, which will be minimized by the PSO.

Also note that the all rotation axis information are normalized vectors (norm$(a) \equiv \hat{a} \equiv a/|a|$), because only the direction information is needed. Other constraints such as locus coverage and minimum number of loci with distinct rotation axis are discussed in depth in Publication I, pp. 1014–1015.

In the ground tests demonstrated in Publication I, $\dot{\omega}_l$ is determined directly from direct observation during the calibration test, where the spacecraft is rotated manually along its spacecraft body axes. Meanwhile, the value of $\hat{n}_{i,l}$ is estimated using orthogonal distance regression plane fitting, where the sum of squared orthogonal distances from the points on the calibrated measurement locus to the plane is minimized. Mathematical tools to solve this least squares problem are well documented, and this paper implements a singular value decomposition (SVD) method\cite{39,46}. A detailed explanation on the SVD implementation is described in Publication I, p. 1015, and the summary can be seen in Algorithm 1.

**Algorithm 1** Algorithm for orthogonal regression plane fitting using SVD\cite{39}.

\begin{enumerate}
\item calculate $\hat{b}_{i,l} = \sum_{s,l=1}^{n_{s,i}} \frac{\hat{b}_{i,s,l}}{n_{s,l}}$
\item construct $A = [\hat{b}_{i,1,l} - \hat{b}_{i,l}, \ldots, \hat{b}_{i,n_{s,i},l} - \hat{b}_{i,l}]$
\item decompose $A = USV^\top$ \hspace{1cm} \triangleright \text{singular value decomposition}
\item find $\text{col}_{\text{min}} = \arg \min_x \{ \text{diag}_x (S) \}$ \hspace{1cm} \triangleright \text{column with minimum singular value}
\item $\hat{n}_{i,l} = U\{ :, \text{col}_{\text{min}} \}$ \hspace{1cm} \triangleright \text{plane normal vector corresponds to the column of minimum singular value}
\item $\hat{n}_{i,l} = \text{sign} (\hat{n}_{i,l} \cdot (\hat{b}_{i,1,l} \times \hat{b}_{i,(2\ldots n_{s,i}),l})) \hat{n}_{i,l}$ \hspace{1cm} \triangleright \text{correction of the plane normal positive direction by comparing it with the measurement sequence}
\end{enumerate}

Finally, the fitness values from the two objectives have to be combined. The MOPSO approach of Publication I applies the fixed weight aggregation technique to combine the fitness values for magnetometer calibration parameters estimation problem because of its simplicity\cite{36}. The total fitness function combines $F_{1,i}$ from eq. (3.9) and $F_{2,i}$ from eq. (3.10) into

$$F_i = c_{f_1} \sqrt{\frac{F_{1,i}}{n_s}} + c_{f_2} \sqrt{\frac{F_{2,i}}{n_l}}$$ \hspace{1cm} (3.11)

where $c_{f_1}$ and $c_{f_2}$ are the fixed weight for each objective. More detailed
process on determining the weight, including an additional step to rectify a mirrored result is available in Publication I, p. 1016.

### 3.2.3 Rotation Axis Fitting with Generic Continuous Random Locus

Instead of grouping multiple magnetic field measurements into a pre-determined number of loci that correlates to a particular rotation plane as proposed in Publication I, which assumes a fixed rotation plane, Publication II updates the method for defining the rotation axis fitting objective in order to accommodate the magnetic field measurement locus of an in-orbit spacecraft, where the rotation mode of the spacecraft does not guarantee a perfectly stable rotation plane(s). The updated method also does not require the fine-tuning of individual weight for each optimization objective, making it more robust under different spin modes and noise levels.

The measurement locus is defined by grouping each continuous measurements as a single locus \( l \), which contains estimated calibrated data \( \hat{b}_{i,l,sl} \), where \( sl = [1, n_{sl} + 2] \) is the index of measurement data in that specific locus. In each locus, a rotation axis vector is estimated from every three magnetometer measurements, as defining a unique plane requires a minimum of three points in 3D space – this means with \( n_{sl} + 2 \) number of measurements in each locus, we can estimate \( n_{sl} \) number of rotation axis. The calculated rotation axis is then compared with reference rotation axis direction using vector dot product in the fitness function

\[
F_{2,l} = \sum_{l=1}^{n_l} \left[ \sum_{sl=1}^{n_{sl}} \left[ 1 - (\hat{n}_{i,l,sl} \cdot \hat{\omega}_{l,sl}) \right]/n_{sl} \right]/n_l,
\]  

(3.12)

where the rotation axis direction for every three measurement points \( \hat{n}_{i,l,sl} \) (subset \( sl \) indexes three-measurements pair in the locus) and the reference rotation axis direction \( \hat{\omega}_{l,sl} \) (averaged over the three measurements period) can be calculated directly with Algorithm 2.

It is important to note that since the rotation axis is estimated with a direct cross product, under ideal condition (zero noise and constant ambient magnetic field), the angular displacement between the two continuous magnetic field vectors \( \hat{b}_{i,l,sl} \) and \( \hat{b}_{i,l,sl+1} \) should not exceed 180°, or the estimated rotation axis vector will be inverted. This also sets the condition of the continuous measurements that can be grouped as a single locus \( l \): the magnetometer sampling rate needs to be at least twice the rotation rate, and delays in measurement interval that exceed half the rotation period should be discarded or grouped into separate locus.

Specifically for Publication II, the reference rotation axis \( \hat{\omega}_{l,sl} \) is obtained directly from gyroscopes measurement \( \hat{\omega} \), which is sampled at the same time as the magnetometer. Alternative reference rotation axis sources discussed in Section 3.2.2 also applies. Thus, the rotation axis fitting
Algorithm 2 Algorithm for rotation axis estimate with direct vector cross product.

1: procedure ROTEST($\hat{b}, \hat{\omega}$)
2: for $i = 1 \ldots n_p$ do ▷ swarm particle $i$
3:     for $l = 1 \ldots n_l$ do ▷ continuous measurement locus $l$
4:         for $sl = 1 \ldots n_{sl}$ do ▷ measurement in the locus $sl$
5:             calculate rotation axis vector with cross product:
6:                 $n_{i,l,sl} = (\hat{b}_{i,l,sl+1} - \hat{b}_{i,l,sl+2}) \times (\hat{b}_{i,l,sl} - \hat{b}_{i,l,sl+1})$
7:             $\hat{n}_{i,l,sl} = \text{norm}(n_{i,l,sl})$ ▷ into unit vector
8:         end for
9:     end for
10: end for
11: end procedure

function $F_{2,i}$ in Equation eq. (3.12) is almost identical with the one defined in Equation eq. (3.10), except that the normalization is included in the fitness function definition instead of in the fitness function combination process. The squaring is also omitted because it doesn’t have to scale directly with $F_1$, as for the implementation in Publication II, $F_1$ and $F_2$ are optimized separately and combined with the sequential refinement process that will be discussed in Section 3.3.7. Consequently, $F_{2,i}$ ranges from 0 to 2.

3.3 PSO Architecture and Parameters

Beyond the basic PSO iteration process, several settings in the swarm topology and parameters are implemented in this thesis work, which are summarized in this section. More detailed description of the algorithm and additional test results can be found in [37].

3.3.1 PSO Topology

The PSO implemented in this thesis is a global topology PSO, where every particle in the swarm can communicate with each other directly, thus enabling an instant propagation of gbest information across the swarm. In contrast, local topology PSOs are also available in different versions[36].
3.3.2 PSO Main Parameters

The main PSO parameters (i.e., $w$, $c_1$, and $c_2$) are implemented with a dynamic parameters adapted from [5]. The details of the adaptation implemented in this thesis work can be found in Publication I, p. 1012, while the summary of this parameters dynamics is depicted in Fig. 3.2.

![Extended parameters dynamics](image)

**Figure 3.2.** Plot of PSO parameters values against the number of iterations, depicting the extended dynamic parameters.

3.3.3 Number of Particles

The number of particles $n_p$ effect on the algorithm performance varies depending on the problem—this is largely remains a trial-and-error problem[4]. In this thesis work, the PSO runs on the swarm size of 30–60 particles.

3.3.4 Initialization Condition

The swarm positions and velocities initial states are determined by $p_{max}$ and $v_{max}$, respectively. For the case of distinct measurement locus approach in Publication I, the initialization range for each component $p_{max,j}$ is estimated around the realistic expected value of the solution, e.g. a range of $[-1, 1]$ for the components of $K_m$ and $[-5000, 5000]$ nT for the components of $k_m$. On the other hand, initialization of the swarm velocities is performed in a similar manner defined by $v_{max}$, which will also be used for the boundary condition. This initialization process can be written mathematically as

$$p_{ij}(k = 0) = p_{max,s,j} + \text{rand}(0, 1)(p_{max,e,j} - p_{max,s,j})$$

(3.13a)

$$v_{ij}(k = 0) = -v_{max,j} + \text{rand}(0, 2)v_{max,j}$$

(3.13b)
where $p_{max,j}$ and $v_{max,j}$ are the individual components of $p_{max}$ and $v_{max}$ for each swarm component $j$, respectively, with the structure $p_{max,j} = [p_{max,s,j}, p_{max,e,j}]$ defining the start and end of swarm position initialization range and $v_{max,j}$ defining the maximum allowed velocity of the swarm. Note that $p_{max}$ can define the swarm positions within any range in the search space, while $v_{max}$ can only define the swarm velocities centered at zero.

For the case of measurement locus from in-orbit attitude dynamics in Publication II, however, the PSO will have to deal with two separate swarms defined in Equation eq. (3.7), and thus these parameters are also set separately for each swarm that corresponds to separate optimization objectives.

For scalar checking objective, the initial positions of $K_{Rm}$ and $k_m$ components are set to 0.1 unit around an identity matrix and 5000 nT around a zero bias vector respectively, or, using the same mathematical notation as eq. (3.5) and eq. (3.7a):

$$p_{max_{K_{Rm}}} = \begin{bmatrix} [0.9, 1.1] & [-0.1, 0.1] & [-0.1, 0.1] \\ 0 & [0.9, 1.1] & [-0.1, 0.1] \\ 0 & 0 & [0.9, 1.1] \end{bmatrix}, \quad (3.14a)$$

$$p_{max_{k_{Rm}}} = \begin{bmatrix} [-5, 5] & [-5, 5] & [-5, 5] \end{bmatrix}^\top \mu T. \quad (3.14b)$$

This represents an a priori estimate of the calibration parameters with very small scaling error and the same initial range of bias error as in the fixed locus version.

For rotation axis fitting objective, the initial positions of $K_{Qm}$ components cover the whole rotation range from 0 to $2\pi$ radians, or, in the same notation as eq. (3.6) and eq. (3.7b):

$$p_{max_{K_{Qm}}} = \begin{bmatrix} [0, 2\pi] & [0, 2\pi] & [0, 2\pi] \end{bmatrix}, \quad (3.15)$$

which allows the swarm to explore every possible rotation sequence combination possible from the beginning.

### 3.3.5 Boundary Condition

The main goal of boundary condition is to limit the swarm search dynamics from ‘exploding’ in the search space. The basic boundary condition which is implemented in this thesis work is the swarm velocity limit represented by $v_{max}$, whose implementation is described in Algorithm 3. Initially, each component of the velocity limit $v_{max,j}$ is set to a value equal with the range of its respective $p_{max,j}$ (i.e., $v_{max,j} = (p_{max,e,j} - p_{max,s,j}) / 2$). Then, the algorithm is evaluated further and checked for consistency using
Algorithm 3 Procedure for limiting swarm velocities.

1: procedure LiMVeL(v, vmax)
2: for i = 1 ... np do  ▷ each particle in the swarm
3:     for j = 1 ... nc do  ▷ each particle component
4:         if |v_{ij}| > vmax_j then  ▷ over speed limit
5:             v_{ij} = sign(v_{ij})v_{max_j}
6:         else
7:             end if
8:     end for
9: end for
10: return v
11: end procedure

A range of $v_{max}$, which is

$$v_{max_j} = \frac{p_{max_e,j} - p_{max_s,j}}{v_{lim}}, \quad v_{lim} = 2 \ldots 30. \quad (3.16)$$

Note that $v_{lim}$ is inversely proportional with the velocity limit imposed on the swarm. This is useful if the actual optimal solution happens to lie outside the initialization range, while limiting the possibilities of swarm explosion\cite{4, 40}.

It is important to note that for the implementation of rotation axis fitting objective in Publication II, the search space of the Euler rotation sequence is a set of three rotation angle, and thus the search space is cyclic between 0 and $2\pi$ radians instead of expanding into infinity. This specific search space boundary characteristic is implemented in order to preserve continuity in the physical representation of the rotation transformation.

3.3.6 Simple Refinement Procedure

Refinement procedure was first proposed in [5] for assisting the swarm in escaping suboptimal solutions in inverse multiple magnetic dipole modeling problem by re-running the algorithm with the initialization region $p_{max}$ set to an a priori knowledge from the previous PSO run solution $gbest(k)$. An overview of this refinement procedure process, adapted for the magnetometer calibration parameters estimation problem, is described in Algorithm 4. Note that a new constant $p_{0,j}$, whose value is determined manually, is defined as the approximated search space around the a priori solution $gbest_j$ for each component $j$.

In Publication I, the refinement procedure is evaluated manually until the fitness value doesn’t show notable improvement. This process is summarized in Fig. 3.3.
Algorithm 4 Refinement procedure.

\[\text{The refinement procedure uses the previous PSO run solution (gbest) as the values of its initialization conditions.}\]
1: procedure \text{REFINE}(gbest, p_0)
2: \hspace{1em} for \(j = 1 \ldots n_c\) do \hspace{1em} \(\triangleright\) for every swarm component \(j\)
3: \hspace{2em} \(p_{\text{max}} j = [gbest_j - p_{0,j}, gbest_j + p_{0,j}]\)
\hspace{2em} \(\triangleright\) define the initial position range
4: \hspace{2em} \(v_{\text{max}} j = (p_{\text{max}} e,j - p_{\text{max}} s,j) / v_{\text{lim}}\)
\hspace{2em} \(\triangleright\) define the velocity limit
5: \hspace{2em} for \(i = 1 \ldots n_p\) do \hspace{1em} \(\triangleright\) for every swarm particle \(i\)
6: \hspace{3em} initialize \(p_{ij}\) and \(v_{ij}\) using eq. (3.13)
7: \hspace{2em} end for
8: \hspace{1em} end for
9: \hspace{1em} \(p_{ij} = \text{randi}(1, n_p) = gbest\)
\hspace{2em} \(\triangleright\) Set one random particle in the swarm equal to previous global best
\hspace{2em} (ensures at least the same fitness value with the previous run)
10: \text{end procedure}

3.3.7 Sequential Objectives Refinement

Publication II implements a different approach in the algorithm that combines the two optimization objectives (represented by \(F_1\) and \(F_2\), which translates to the best swarm \(gbest_1\) and \(gbest_2\), respectively) and evaluates the termination condition when compared to Publication I: instead of optimizing the weighted addition of the two fitness values in one PSO iteration, each PSO run, as summarized in Fig. 3.1, will optimize the two objectives alternatingly and combine the results using a heuristic which will recognize stagnation in the fitness value as the final termination condition. This approach also negates the need for manually tuning the weight for each fitness value under different measurement conditions.

This is implemented by adapting the same refinement procedure from Algorithm 4 into a sequential objective refinement procedure. Detailed explanation of this procedure can be found in Publication II, pp. 5–6, while the complete summary can be seen in Fig. 3.4.
Start

Initiate PSO:
- set $k_{\text{max}}$
- set boundary $p_{\text{max}}$ and $v_{\text{max}}$
- initiate $w, c_1, c_2$
- initiate $p_i, v_i$: eq. (3.13)
- evaluate $p_{\text{best}}$: eq. (3.2a)
- evaluate $g_{\text{best}}$ and $F_{\text{gb}}$: eq. (3.2b) and eq. (3.2d)

Set objective: $F$ eq. (3.11)

Refinement loop

Refine($g_{\text{best}}, p_0$):
Algorithm 4

yes

Main PSO: Fig. 3.1

Recompute? yes no END

Figure 3.3. Flowchart for the complete MOPSO with simple refinement loop.

Start

Initiate Sequential Refinement:
- stagnancy flag $stag = 0$
- set objective to $F_1$ eq. (3.9)

Objective switch loop

- stag = 1
  - Switch objective:
    eq. (3.9)$F_1 \leftrightarrow F_2$eq. (3.12)

Initiate PSO:
- set $k_{\text{max}}$
- set boundary $p_{\text{max}}$ and $v_{\text{max}}$
- initiate $w, c_1, c_2$
- initiate $p_i, v_i$: eq. (3.13)
- evaluate $p_{\text{best}}$: eq. (3.2a)
- evaluate $g_{\text{best}}$ and $F_{\text{gb}}$: eq. (3.2b) and eq. (3.2d)

Main PSO: Fig. 3.1

$\Delta F = |F_{\text{previous}} - F_{\text{now}}|$

- stag = 0
  - Refine($g_{\text{best}}, p_0$):
    Algorithm 4

no yes

$stag = 1$?

Figure 3.4. Flowchart for the complete PSO with sequential objective refinement.
4. Verification of PSO Algorithm with Rotation Correction Factor

The PSO algorithm is tested with simulations, ground test, and real in-orbit flight data. The simulated data will emulate both the ground test condition as well as the condition of the real in-orbit data, so that the result can be evaluated against the known simulated calibration error.

For the ground test data using the simple refinement MOPSO, several type of measurement locus and data quality are simulated to evaluate the algorithm robustness and the general accuracy is evaluated from the direct difference between the estimated calibration parameters and the simulated model.

For the in-orbit data using the sequential objective refinement PSO, the algorithm is verified on several type of simulated attitude dynamics and spin mode. The main evaluation metric for the simulation results is the accuracy of the rotation correction matrix $K_{Qm}$, which can be calculated directly by converting the rotation matrix into axis-angle representation and taking the angular component\[^{47}\]:

$$\tilde{\theta} = \arccos \left( \frac{\text{trace}(K_{Qm}S_{Qm}) - 1}{2} \right), \quad (4.1)$$

where $S_{Qm}$ is the orthogonal matrix from QR-decomposition of the known magnetometer error matrix model $S_m$.

4.1 Data Simulations

Algorithm verification is performed using set of simulated data that emulate different conditions during ground test and in-orbit measurement. In ground test emulation, the magnetic field measurement locus is fixed on predefined 3-D planes. For in-orbit data emulation, a full orbit and attitude dynamics simulation with Earth magnetic field model is implemented in order to simulate magnetometer measurement.
4.1.1 Simulated Fixed Measurement Locus

The PSO algorithm (simple refinement MOPSO variant) is evaluated using the magnetometer model from eq. (2.2a) under a simulated environmental condition that will be experienced by Aalto-1 satellite\[22\]. Aalto-1 planned altitude is around 500–900 km, and IGRF12 model\[13\] shows a geomagnetic field variation of approximately 17 000–48 000 nT on the average altitude of 700 km.

The algorithm is then tested with several model variations summarized together with their respective estimated model errors in Table 4.1. Additionally, estimated parameters using Extended Kalman Filter (EKF) described in [6] is included as a performance comparison under model 1. The graphical representations of the measured, calibrated, and true magnetic field vector locus for some model variations (selected for brevity) are given in Fig. 4.1. More detailed numbers on the estimated model parameters, including in-depth discussion on the algorithm performance and limitations can be found in Publication I, pp. 1016–1017.

Table 4.1. Error range of estimated model parameters from different simulation models.

<table>
<thead>
<tr>
<th>MODEL VARIANT</th>
<th>(\hat{S}_{m_e}) [nT]</th>
<th>(\text{off}_{m_e}) [nT]</th>
<th>(F_p)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODEL 1, EKF:</td>
<td>(n_l = 3,</td>
<td>b</td>
<td>= 35,000\text{ [nT]}, \delta = 2000\text{ [nT]})</td>
</tr>
<tr>
<td>MODEL 1, PSO:</td>
<td>(n_l = 3,</td>
<td>b</td>
<td>= 35,000\text{ [nT]}, \delta = 2000\text{ [nT]})</td>
</tr>
<tr>
<td>MODEL 2, PSO:</td>
<td>(n_l = 3,</td>
<td>b</td>
<td>= 35,000\text{ [nT]}, \delta = 5500\text{ [nT]})</td>
</tr>
<tr>
<td>MODEL 3, PSO:</td>
<td>(n_l = 2,</td>
<td>b</td>
<td>= 35,000\text{ [nT]}, \delta = 2000\text{ [nT]})</td>
</tr>
<tr>
<td>MODEL 4, PSO:</td>
<td>(n_l = 2,</td>
<td>b</td>
<td>= 17,000–48,000\text{ [nT]}, \delta = 2000\text{ [nT]})</td>
</tr>
<tr>
<td>MODEL 5, PSO:</td>
<td>(n_l = 3 \text{ (incomplete circle)},</td>
<td>b</td>
<td>= 35,000\text{ [nT]}, \delta = 2000\text{ [nT]})</td>
</tr>
</tbody>
</table>

4.1.2 Simulated In-Orbit Measurements

The algorithm is verified on simulated data that emulate the orbit and attitude dynamics of Aalto-1\[33\] and ESTCube-1\[23\] in-orbit condition, i.e. the simulation will replicate the orbit parameters and physical properties of each spacecraft, including the Earth magnetic field model. Additionally, the algorithm is verified on a baseline model, which represents "best case" condition for algorithm performance.

All three sets of simulations are run under varying initial spin rate and noise level; details on the different combination of simulation models,
Verification of PSO Algorithm with Rotation Correction Factor

\[ y[nT] \times 10^4 \]
\[ x[nT] \times 10^4 \]
\[ z[nT] \]
\[ x[nT] \times 10^4 \]
\[ y[nT] \times 10^4 \]
\[ z[nT] \]
\[ x[nT] \times 10^4 \]
\[ y[nT] \times 10^4 \]
\[ z[nT] \]

(a) Model 1: three circle loci, constant ambient magnetic field magnitude.
(b) Model 4: two circle loci, gradually increasing ambient magnetic field magnitude.
(c) Model 5: three incomplete circle loci, constant ambient magnetic field.

Figure 4.1. 3-D plot of magnetic field vectors from simulation comparing the measured, calibrated, and true magnetic field vector data points. All modeled with magnetometer noise standard deviation \( \delta = 2000 \text{nT} \).

initial conditions, and noise levels are available in Publication II, pp. 6–7. The rotation correction accuracy calculated from eq. (4.1) for every model is shown in Fig. 4.2.

4.2 Ground Tests

The experimental test was performed for the engineering model (EM) of Aalto-1 nanosatellite at a magnetic test facility operated by Finnish Meteorological Institute (FMI) located in Nurmijärvi, Finland\(^{[17]}\), depicted in Fig. 4.3. The Helmholtz cage manipulates the ambient magnetic field to a desired value, so that the estimated calibration parameters can be evaluated under different conditions.

Using the known angular reference from the initial orientation data (note that this is unfiltered data), it can be calculated that the heading error of the magnetometer improved from 5.24–13.24° before calibration to 1.9–7.3° after calibration. Detailed analysis on the ground test results can be found in Publication I, p. 1018.
Verification of PSO Algorithm with Rotation Correction Factor

Figure 4.2. Plot of rotation correction accuracy $\tilde{\theta}$ against the spacecraft initial spin rate for varying noise level (noise level index available in Publication II).

4.3 Flight Data

The calibration algorithm is implemented on the in-orbit data of Aalto-1 and ESTCube-1 missions.

4.3.1 Calibration of Aalto-1 In-orbit Data

Aalto-1 satellite attitude is mostly in a tumbling state around its major or minor axis; this will be discussed in more detail in chapter 6, which encompasses the work in Publication III and Publication IV. Detailed conditions of the spacecraft dynamics and other measurement characteristics, including the estimated calibration results are available in Publication II, pp. 7, 9. The final calibration matrix can be decomposed into the rotational component $K_{Qm}$, which corresponds to a $8.13^\circ$ angular correction when converted to axis-angle form. The magnetic field measurement locus before and after calibration are shown in Fig. 4.4a.

4.3.2 Calibration of ESTCube-1 In-orbit Data

ESTCube-1 satellite attitude is largely dominated by the torque from the RMM of the spacecraft, resulting in its magnetometer reading mostly pointing in one side of the spacecraft\cite{43, 42, 10}. Detailed information on spacecraft dynamics and measurement characteristics, as well as the calibration results are available in Publication II, pp. 7, 9. The rotational component $K_{Qm}$ of the calibration matrix for ESTCube-1 corresponds to a $2.137^\circ$ angular correction in axis-angle form. The magnetic field measurement locus before and after calibration are shown in Fig. 4.4b.
Verification of PSO Algorithm with Rotation Correction Factor

Figure 4.3. The magnetic test facilities with Helmholtz cage setup in Nurmijärvi Geo-physical Observatory, operated by Finnish Meteorological Institute. The specifications of the test setup are available in [17].

Figure 4.4. 3-D scatter plot magnetic field vectors, showing the measured and calibrated data points. The sphere grid is set at a radius equal to the maximum magnetic field magnitude of the Earth magnetic model during measurement.
5. Development of machine-vision-assisted test bed for magnetic dipole estimation

5.1 Estimation of Spacecraft Magnetic Properties with Inverse MDM

As described in Section 2.3, MDM describes the set of magnetic field generated by multiple magnetic dipole moments. In order to investigate the spacecraft residual magnetic moment, a process called inverse MDM is used for estimating the multiple magnetic moments (i.e. their positions $p_d$ and moment vectors $m_d$) given a set of magnetic field measurements (i.e. the sensor positions $p_s$ and the measured magnetic field $b_s$). In this thesis work, the implemented approach is by minimizing the (least squares) error between the estimated magnetic field $\hat{b}_s(p_s, \hat{p}_d, \hat{m}_d)$ and its actual measurement $\tilde{b}_s(p_s, \tilde{p}_d, \tilde{m}_d)$.\cite{11, 27}

PSO implementation for inverse MDM problem. Different algorithms are available in literature for solving the minimization problem in inverse MDM\cite{5, 20, 26, 27}. In this thesis work, a MOPSO algorithm with identical implementation as described in Fig. 3.3 is used, except for the fitness function definitions. The fitness functions are adapted from [5], which are

$$F_{1,i} = \frac{\sqrt{\sum_{s=1}^{n_s} \left[ (\tilde{b}_{x,s} - \hat{b}_{x,i,s})^2 + (\tilde{b}_{y,s} - \hat{b}_{y,i,s})^2 + (\tilde{b}_{z,s} - \hat{b}_{z,i,s})^2 \right]}}{\sqrt{\sum_{s=1}^{n_s} \left[ b_{x,s}^2 + b_{y,s}^2 + b_{z,s}^2 \right]}}$$  (5.1)

and

$$F_{2,i} = \frac{\sum_{s=1}^{n_s} \left[ (\tilde{b}_{x,s} - \hat{b}_{x,i,s})^2 \right]}{\sum_{s=1}^{n_s} \hat{b}_{x,s}^2} + \frac{\sum_{s=1}^{n_s} \left[ (\tilde{b}_{y,s} - \hat{b}_{y,i,s})^2 \right]}{\sum_{s=1}^{n_s} \hat{b}_{y,s}^2} + \frac{\sum_{s=1}^{n_s} \left[ (\tilde{b}_{z,s} - \hat{b}_{z,i,s})^2 \right]}{\sum_{s=1}^{n_s} \hat{b}_{z,s}^2}$$  (5.2)
where
\[
\hat{b}_s \equiv \begin{bmatrix} \hat{b}_{x,s} & \hat{b}_{y,s} & \hat{b}_{z,s} \end{bmatrix}^T \quad \text{and} \quad \hat{b}_{i,s} \equiv \begin{bmatrix} \hat{b}_{x,i,s} & \hat{b}_{y,i,s} & \hat{b}_{z,i,s} \end{bmatrix}^T,
\]
while the subscripts \( s \) and \( i \) represent the indexes for measurement point and swarm particle, respectively. These fitness functions are combined using a dynamic weight aggregation method in the form of
\[
F_i(k) = \left( \frac{F_{1,i}(k-1)}{F_{2,i}(k-1)} \right) F_{1,i}(k) + \left( \frac{F_{2,i}(k-1)}{F_{1,i}(k-1)} \right) F_{2,i}(k),
\]
where the combined fitness value at \( k \)-th iteration is dynamically weighted using the fitness value from previous iteration.

The PSO search space itself is constructed from the magnetic dipole position and moment vectors elements
\[
\hat{p}_{i,d} \equiv \begin{bmatrix} \hat{p}_{x,i,d} & \hat{p}_{y,i,d} & \hat{p}_{z,i,d} \end{bmatrix} \quad \text{and} \quad \hat{m}_{i,d} \equiv \begin{bmatrix} \hat{m}_{x,i,d} & \hat{m}_{y,i,d} & \hat{m}_{z,i,d} \end{bmatrix}
\]
into
\[
\hat{p}_i = \begin{bmatrix} \hat{p}_{x,1,i} & \hat{p}_{y,1,i} & \hat{p}_{z,1,i} & \hat{m}_{x,1,i} & \hat{m}_{y,1,i} & \hat{m}_{z,1,i} & \cdots & \hat{p}_{x,n_d,i} & \hat{p}_{y,n_d,i} & \hat{p}_{z,n_d,i} & \hat{m}_{x,n_d,i} & \hat{m}_{y,n_d,i} & \hat{m}_{z,n_d,i} \end{bmatrix}^T.
\]
This format means the swarm dimension is \( n_c = 6n_d \) because each magnetic dipole is defined with 6 elements. The number of dipoles \( n_d \) itself has to be estimated manually outside the PSO algorithm, which can be determined by evaluating the fitness function as described in [5].

### 5.2 Inverse MDM Data Acquisition Test Bed

Gathering the magnetic field data set required for inverse MDM typically involves a test bed that includes a Helmholtz cage and a sensitive magnetometer. The Helmholtz cage is used for neutralizing the Earth’s ambient magnetic field, so that the magnetometer can read the magnetic field generated from the RMM of the device-under-test (DUT) in a controlled environment. The magnetometer also needs to be sensitive enough to read the magnetic field generated by the DUT, which scales down with distance to the power of three as indicated in eq. (2.4).

In order to automate this data acquisition process, typically the DUT is rotated (and/or moved around) with known displacement, while the measurement magnetometer is placed in several spots (with one or several moving magnetometer) with known position and attitude as such that the measurement points cover all directions (ideally) around the DUT. In magnetic test facilities such as in ESA’s Noordwijk site, among others, automated turntable is used to rotate the DUT while the magnetometer is moved around along rails (or multiple magnetometers is placed
statically)\textsuperscript{11, 32, 5}. As discussed in Section 4.2, the magnetic test facility operated by FMI in Nurmijärvi is used for magnetometer calibration of Aalto-1 EM (as shown in Fig. 4.3), and the same facility was used for magnetic dipole estimation of Aalto-1\textsuperscript{37}, but the system was not automated and the data acquisition process can take hours to complete.

**Machine-vision-assisted data acquisition.** For this work, an automated test bed is developed in Aalto University’s space lab; it is equipped with a Helmholtz cage and data acquisition system that will report the relative positions between the DUT and the magnetometer, as well as the magnetic field vector measured at each of the magnetometer positions. To achieve this, a visual marker detection system using camera based on the ArUco marker\textsuperscript{15, 38} is used for reporting the position and orientation of both the DUT and magnetometer during the magnetic field measurement. Using these information, the position and direction of each magnetic field measurements can be translated into the DUT coordinate frame, which is equivalent with $p_s$ and $b_s$ from eq. (2.4), respectively.

Because the position and orientation information are collected externally by the camera, a turntable with closed-loop controllable angular displacement for the DUT and position manipulator for the magnetometer is not necessary. Instead, the magnetometer is placed statically inside the Helmholtz cage, while the DUT can move and rotate freely. For this work, manipulation of the DUT is done freely by hand.

This machine-vision-assisted data acquisition setup eliminates the mechanical and electrical complexity involved with the installation of automated turntable and magnetometer position manipulation mechanisms. Because the magnetometer is placed statically inside the Helmholtz cage, magnetic field variations from the Helmholtz coils can also be minimized. Additionally, the elimination of electrical complexity (e.g. motors for the turntable and magnetometer manipulator) means less source of potential magnetic disturbance. However, the accuracy of position and attitude data of the DUT and magnetometer is limited by the camera and the performance of ArUco detection algorithm.

### 5.3 Test Bed Technical Performance

The test bed developed in this thesis work involves a DUT that is covered by ArUco markers on different sides and a measurement magnetometer with one ArUco marker fixed to it. All the components are placed in a Helmholtz cage that neutralizes the Earth magnetic field. The DUT is then freely moved and rotated by hand so that the magnetometer is measuring the magnetic field around the DUT, covering most direction at various distances. The same procedure is then performed on the tether motor of Foresail-1 EPB payload\textsuperscript{29, 16} in order to determine the RMM of the motor,
as well as on the complete EPB module with a compensating permanent magnet. This test setup can be seen in Fig. 5.1; note that the DUT pictured is the EM of Foresail-1 EPB module.

![Test components inside a Helmholtz cage.](image)

(a) From left to right: DUT, magnetometer, and camera module.

(b) Test components inside a Helmholtz cage.

**Figure 5.1.** Machine-vision-assisted data acquisition test bed in Aalto University Space Lab.

### 5.3.1 Performance Verification on Known Magnetic Dipoles

In this work, a preliminary verification of the test bed technical performance is conducted by performing the measurement procedure on a set of permanent magnets with known magnetic dipole as the DUT. The magnets are mounted on a cube-shaped harness ($5 \times 5 \times 5$ cm) which is then covered with ArUco markers on all sides. The DUT coordinate frame’s origin is defined at the center of marker 1, as shown in Fig. 5.2.

![Coordinate frame of the DUT, covered with ArUco markers.](image)

**Figure 5.2.** Coordinate frame of the DUT, covered with ArUco markers.

The verification test is conducted on two configurations:

1. One magnet mounted $\approx 5$ mm behind marker 1, with its polarity parallel the $z$-axis.

2. Two magnets; one mounted at the same position as configuration 1
but opposite polarity; another one mounted behind marker 2, rotated 90° from the first magnet.

The estimated dipole moment vectors along with the measured magnetic field vectors are shown in Fig. 5.3, and the error of the estimated dipole positions and magnetic moments is summarized in Table 5.1. This shows a position estimate accuracy of at least $< 10 \text{mm}$ and dipole magnitude accuracy of around $< 15 \text{mAm}^2$.

![Diagram showing estimated magnetic moment vectors and measured magnetic field vectors.](image1)

(a) One magnet configuration.  
(b) Two magnets configuration.

**Figure 5.3.** 3D plot of estimated magnetic moment vectors and measured magnetic field vectors from known permanent magnets.

| CONFIGURATION       | $\vec{p}_d$ [mm] | $\vec{b}_d$ [mAm$^2$] | $|\vec{b}_d|$ [mAm$^2$] |
|---------------------|------------------|------------------------|-------------------------|
| 1 magnet            | $[-0.85 -9 -0.06]^T$ | $[-6.3 -1.6 -6]^T$ | 5.6                     |
| 2 magnets: magnet #1| $[3.2 0.05 -7.2]^T$ | $[15.5 -2.9 -12]^T$ | 13.9                    |
| 2 magnets: magnet #2| $[0.1 -3.4 -0.6]^T$ | $[-19.7 3.3 11.8]^T$ | 7.9                     |

**Table 5.1.** Error between estimated and known dipole positions and magnetic moments of the permanent magnets.

### 5.3.2 RMM Estimation and Compensation of Foresail-1 Plasma Brake

For estimating its RMM, the EPB tether motor is mounted on a harness identical with the one in Fig. 5.2; a cutout drawing of the harness and motor along with the motor coordinate frame is depicted in Fig. 5.4. The compensated-RMM test, however, is performed on a complete EPB module, which can be seen as the leftmost device in Fig. 5.1a; in this case, a permanent magnet with similar magnetic moment (but reversed polarity)
as the EPB tether motor RMM is placed underneath the front marker, which should be in line with the motor \( z \)-axis.

![Figure 5.4. EPB tether motor coordinate frame on a centered cutout drawing of the motor inside the test harness.](image)

The 3D plot of the EPB tether motor and the complete EPB module (with compensating magnet) RMM estimate is shown in Fig. 5.5. The EPB tether motor test shows that the motor RMM is located almost in the center of the motor (\( \approx 25.5 \text{ mm} \) from the motor frame origin) with a magnitude of 56.2 mAm\(^2\). Using the RMM estimate from the standalone EPB tether motor test and the compensating magnet specification as the known reference, the estimation difference with the complete EPB module can be calculated; this is summarized in Table 5.2. This result shows similar accuracy with the verification tests using permanent magnets for the dipole position estimate, while the dipole moment estimate shows larger error than expected.

| DIPOLE SOURCE          | \( \hat{p}_d \) [mm]   | \( \hat{b}_d \) [mAm\(^2\)] | \(|\hat{b}_d|\) [mAm\(^2\)] |
|------------------------|------------------------|-------------------------------|--------------------------|
| EPB motor              | \([-9.7, 1.2, -0.7]\)\(^T\) | \([22.3, 8.8, -17.1]\)\(^T\) | 24.5                     |
| Compensating magnet    | \([1.9, -1.6, -1.3]\)\(^T\) | \([-25, -12.1, 7.6]\)\(^T\)  | 13.4                     |

### 5.3.3 RMM Estimation of Foresail-1 Magnetorquer Coil

Similar test setup as previous tests is used in order to verify the magnetic moment produced by the magnetorquer coils designed in Publication V. The major difference is the physical dimension of the DUT, which in this case is the long coil attached to the Y–side solar panel of Foresail-1 EM.

The 3D plot of estimated dipole and measured magnetic field vectors is shown in Fig. 5.6. Note that although the DUT is a single coil, its rectangu-
Development of machine-vision-assisted test bed for magnetic dipole estimation

Figure 5.5. 3D plot of estimated magnetic moment vectors and measured magnetic field vectors from the compensated EPB module tests.

Figure 5.6. 3D plot of estimated magnetic moment and measured magnetic field vectors from the Y- side magnetorquer coil of Foresail-1 EM at 3.9 V.

lar dimension (≈ 60 × 260 mm$^2$) means that a single dipole representation results in a poor fitness value; minimum fitness value is achieved with 4 dipoles model, and the magnitude of the combined magnetic dipole moments is ≈ 150 mA m$^2$ when the coil is powered at 3.9 V. This is within the test bed estimation error compared to the specification described in Publication V, p. 11, which is 304 mA m$^2$ at 3.6 V for a pair of coils in one axis.
6. Practical in-orbit attitude performance of Aalto-1

Publication III reports the overall technical performance of Aalto-1 CubeSat subsystems and payloads in orbit, as well as the challenges faced during its operation. The Aalto-1 ADCS in particular faced several challenges that made it difficult to fulfill the mission goals. From the beginning, the commissioning phase of the ADCS functions were met with complications, as two of the sun sensors (on the $+x$ and $-x$ directions of the satellite) malfunctioned and did not produce useful data for attitude estimation. Testing the ADCS functionalities also took longer time than expected as the debugging procedure turns out to be complicated and time-consuming—this problem also gets magnified as the operation time needs to be managed between the different subsystems and payloads.

In long-term operation of the ADCS, the ADCS module is mostly limited to gyroscopes and magnetometers reading with limited attitude estimation capability, while the control is limited to detumbling control, i.e. reducing the spin rate of the spacecraft close to zero. The detumbling was possible as the B-dot control does not require attitude estimation in the control loop. However, the spacecraft will naturally spin up due to the disturbance torque if the detumbling control is turned off. The magnetometers and gyroscopes were finally confidently calibrated after cross-checking the long-term data of each sensor. The long-term data on Aalto-1 spin mode, which is also discussed in more details in Publication III, can be seen from the gyroscopes data shown in Fig. 6.1.

Overall, some goals in ADCS performance set by the payload operational requirements can only be met in a limited scope. The EPB payload on Aalto-1 requires a spin-up maneuver around certain axis, which could not be achieved actively with active control. However, the natural spin-up of the spacecraft into a spin-stabilized mode allows some deployment testing of the EPB tether. The Radiation Monitor (RADMON) payload would benefit more from real-time information of full attitude knowledge during the measurement period, but the limited ADCS functionality means that the useful information for the scientific data of RADMON was limited to the variations of RADMON’s boresight pitch angle relative to the local
Figure 6.1. Calibrated gyroscopes data for three orthogonal axes of Aalto-1 satellite between summer 2017 and 2020.

magnetic field, where this issue is discussed in more details in Publication IV.

The magnetometer calibration algorithm developed for this thesis work, as described in chapter 3 and implemented on Aalto-1 satellite flight data discussed in chapter 4, has been proven in practical application. However, in the case of Aalto-1, its usefulness in the overall ADCS technical performance is limited, as many of the ADCS functionalities are not working properly. A lot of these difficulties stemmed from a combination of factors, from the partial failure of some sensors, unthorough testing of the fully-assembled system on the ground (where debugging is more accessible), limited capability of on-orbit debugging of the ADCS module, to the operational aspect of the spacecraft that stretched the time needed to resolve technical problems.
This thesis highlights the influence of magnetic environment in nanosatellites ADCS, more specifically for the active calibration of magnetometers and management of error sources from the spacecraft residual magnetic moment dipole. This thesis also highlights some of the challenges in ADCS analysis, particularly from the problems encountered during the operation of Aalto-1 satellite. The development of calibration algorithm serves to resolve the rotational error of the magnetometers using the information that can be extracted from the spacecraft in orbit environment. Management of magnetic error source from the spacecraft RMM is achieved by the development of automated test bed in Aalto University, where a machine vision technique is used in automating the data acquisition process.

In magnetometer calibration, Publication I describes a novel approach that improves existing scalar-checking-based PSO algorithm. The improved PSO is designed to estimate a full $3 \times 3$ distortion matrix and $3 \times 1$ bias vector (a total of 12 parameters) by implementing a new rotation axis fitting objective, which requires the knowledge of the magnetometer rotation axis to resolve the rotation correction factor contained in a full $3 \times 3$ distortion matrix.

The algorithm performance is verified with simulated and ground test data from the EM of Aalto-1 satellite mission. Simulated data shows that the algorithm is capable of accurately estimating the calibration parameters. In simulated data without modeled rotational error component, the calibration accuracy is on par with existing algorithm such as EKF at the cost of non real-time performance. However, the algorithm is designed to resolve rotational error when present in the magnetometer reading, where the accuracy definitely improved from existing, scalar-checking-only algorithms. Ground tests showed similar consistency with the simulated data, particularly for data with high noise level. The algorithm is also capable of estimating the calibration parameters under varying ambient magnetic field magnitude as well as incomplete circle measurement loci. Overall, the resulting accuracy is affected by data quality, such as small number of data points, unbalanced loci in one side of the sphere, and noise.
Conclusions

In Publication II, the calibration algorithm is improved further using a more general curve fitting algorithm. The goal is to relax the requirements on the measurement locus definition, so that the algorithm can fit the data collected under free-rotating dynamics of a spacecraft in orbit. This is based on the improvement of the rotation axis fitting method and a novel approach in the integration of the two optimization objectives using a sequential objectives refinement process. The accuracy of the rotation correction factor from the calibration result has been validated using simulated data with in-orbit spacecraft dynamics. In best cases, rotation accuracy in the order of 0.1 degree between the magnetometer and the reference rotation axis can be achieved under reasonable noise level.

There are three main factors that determine the quality of the data for calibration: rotation mode of the spacecraft, spacecraft spin rate, and sampling rate of the sensors (magnetometer and the sensor for reference rotation axis). The rotation mode and spin rate determine the variation of rotation axis due to the attitude dynamics, where the algorithm prefers a significant angle of nutation or using attitude control to change the rotation axis. The sensor sampling rate should be at least two times faster than the rotation rate. In a condition with high nutation angle and rate, the sampling rate also need to be higher than the oscillation of the spin rate. In general, higher sampling rate improves accuracy, especially in the presence of noise, as the natural change of magnetic field direction along the orbit lowers the accuracy on lower spin rate.

In the case of in-orbit data of Aalto-1 and EstCube-1 missions, the measurements does not always fulfill the ideal conditions desired from the spacecraft attitude dynamics. To achieve higher confidence in the calibration results, active attitude control can be used to manipulate the attitude dynamics during data collection.

The calibration process can be improved further by accounting for other error sources in the magnetometer and calibration reference sources. This could come from the combination of orbit estimation and IGRF model inaccuracies for the scalar-checking, and additional uncertainties in gyroscope data for the rotation axis fitting. Magnetometer model could also include time-varying factors such as the influence of spacecraft structure and electronics.

Attitude maneuver simulations in Publication V shows how the attitude system performance can be affected by different variables in magnetorquer design. Spacecraft RMM, which generates disturbance torque, will further affect the system performance. In order to devise a strategy in managing the spacecraft RMM, a good estimation of the spacecraft RMM is required. Preliminary verification and RMM analysis has been conducted using the machine-vision-assisted test bed developed in this thesis work. While certain figures of accuracy can be achieved with this test setup, the scalability
Conclusions

is not yet investigated; this will become relevant when the same RMM analysis procedure is performed on a complete spacecraft, especially for bigger spacecraft. This is evident, as, during the tests, the ArUco marker detection results contain non-random errors that scale and correlate with the distance from the camera, size of marker, and marker orientation relative to camera. These errors get carried into the data used in the inverse MDM algorithm, resulting in different accuracy of the RMM estimate.

In order to improve the performance of the test bed and estimation algorithm, many areas of the test procedure can be improved: determining the optimal combination of camera distance, marker size, and preferred marker rotation/orientation to minimize systematic error; better data fusion heuristics/filter for combining the information from the detection of multiple markers and/or multiple cameras setup; and algorithm improvement for the inverse-MDM process.

In the hands-on, practical perspective of the ADCS operation and performance evaluation related to some of the analysis in Publication III and Publication IV, the important lessons learned was to perform a rigorous functionality test campaign during the integration of the different subsystems, as well as a thorough testing of the operational aspect of the mission. Another factor to consider is the proper integration of the troubleshooting process of COTS and in-house built subsystems, as the access to fully debug a ready-made COTS modules can be very different from an in-house built ones.

To summarize, this thesis has provided a new magnetometer calibration algorithm that incorporates rotation correction factor in a spacecraft setting, as well as an initial development of a machine-vision test bed for spacecraft RMM measurement. Besides verifying the calibration algorithm using simulated data, this thesis work also includes in-orbit analysis of the proposed algorithm performance. For future works, more testing and characterization of the RMM estimation test bed performance should be investigated. For magnetometer calibration algorithm, further development might involve more advanced method in defining the reference rotation axis in the rotation axis fitting method, as current implementation only uses direct data from spacecraft gyroscope.


The development of nanosatellites have seen rapid growth in the academia sector, especially in the CubeSat category. The majority of these nanosatellites are orbiting in Low Earth Orbit, where the magnetic environment is an important aspect in its design consideration. Specifically, magnetic environment could have a major influence on the spacecraft attitude system design as well as the design of the relevant scientific instruments.

This thesis work contributes in the development of technologies and techniques that can help in managing the influence of magnetic environment in spacecraft design: an algorithm for magnetometer calibration, development of automated test bed to measure spacecraft residual magnetic dipole moment, and attitude analysis related to magnetorquer design for attitude actuation. The work also provides validation of the proposed methods and insight to CubeSat in-orbit magnetic environment by analysing data from several missions, as well as discusses practical aspects of CubeSat development based on Aalto University CubeSat missions.