

Improved Range-Only Beacon Initialization Towards Localization System

Molaletsa Namoshe, Oduetse Matsebe, Ngatho Tlale

Abstract—Mobile robot operation in an un-surveyed environment presents a challenging problem, particularly in GPS denied spaces. The complexity of the problem scales up if the sensor used to aid navigation can only provide range information about the features in that environment. In the past, almost all solutions to Localization problems relied on a prior knowledge of feature locations. In this paper however, range measurements, characteristically known to have outliers and unobservable are used to solve the localization problem. Past approaches to this problem have used delayed initialization of newly observed feature(s) until good estimates are available; a process akin to Hough transforms methods. This ratio thresholding approach has shown to be susceptible to system divergence, especially when large environments are explored. In this paper therefore, a pose disambiguating algorithms comprising of outlier rejection, particle swarm optimization (PSO) and an area under a probability distribution function (pdf) methods are used to solve the localization system using real data acquired by a mobile robot in an unknown space. To validate the proposed methods, experimental real data sets obtain by *Odyssey III* during the GOATS'02 experiments are used.

Index Terms— Range data, Gaussian distribution, Localization, feature initialization, Beacon (feature/ landmark), and observation sensor.

I. INTRODUCTION

Relatively few works in the field of robot navigation have addressed the problem of localization with range only (RO) sensors, in despite of their past important applications in underwater autonomous vehicle [1] and industrial material handling robots [2]. Equipped with an on-board sensor, a mobile robot platform is able to estimate range to stationary acoustic transponder beacons by sending a ping and measuring the time of flight when a response message is registered by the receiver. These range information designate the existence of beacons in the environment which can be initialised and used to aid localization system. Localization system is a sub-field of Simultaneous Localization and Mapping (SLAM) which makes an assumption that an observation sensor on a moving robot can measure range and bearing to features of interest in its vicinity [3]. SLAM solutions has been likened to a “chicken and egg problem”, which states that a robot can localize itself using features in the map and an observation sensor; conversely, using best position estimates of the robot, a map of these features can be constructed [4,5 and 6].

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Molaletsa Namoshe, College of Engineering, Department of Mechanical & Energy Engineering, Botswana International University of Science & Technology, Palapye, Botswana.

Oduetse Matsebe, College of Engineering, Department of Mechanical & Energy Engineering, Botswana International University of Science & Technology, Palapye, Botswana.

Ngatho Tlale, Transnet, Carlton Centre, 150 Commissioner Street, Johannesburg, South Africa.

In range only localization system however, the “map” is simply the location of these features. Despite best promise offered by range data autonomous navigation, there are two major reasons rendering RO localization system a difficult problem to solve. These include: (a) partial observability of the feature locations given range measurements and (b) the existence of outliers in range data measurements. Typically, localization systems use both robot and feature locations to update system position estimates using a single measurement to linearize around a prior. In the case of RO data however, linearization about a prior and a single feature observation process cannot be used. The reason been that, there is no prior knowledge of the feature positions and that a single measurement of the beacon is not enough to estimate feature location. In this paper we present an improved method for estimating a beacon location (beacon initialization) given a few range measurements, i.e. the ability to disambiguate feature location after a few measurements. The proposed methods first applies an outlier rejection algorithm, then uses PSO as a pose disambiguating algorithm and finally use area under the probability graph as confirmation tool. The result of the PSO algorithm and the area under the probability density function graph must be consistent.

II. RELATED WORK

Navigation solutions using range only data has not been extensively researched, there is however a small number of important published work in the area, with more focus on solving the SLAM problem. In one of the previous proposals for using range only data for navigation in [7], authors reports the use of geometric method for initializing newly observed features using delay technique to initialize features in the map. This method requires partially known map from the start of the system and does not mention cases where a map is not known. Another work approached the work from a global sense [8], and gives a brief account of cases where feature locations are unknown. In this work the authors assume that the beacon locations are approximately known, it also fails mention cases where no prior knowledge is available. The work in [9] uses a Hough transform kind of approach where initial estimation of each features are voted into a 2D grid accumulation array. A similar scheme is adopted [10], but the work explored the possibility where features (nodes of a sensor) are able to make beacon to beacon range measurement. Work presented by [11] is similar to our work in that they use spectral graphical partitioning [12, 13 and 14] for outlier rejection but their voting scheme method assumes a 2:1 ratio thresholding technique to disambiguate feature location. Thresh holding method employed turns to cause significant delay time until the ratio is attained, leading to possible system divergence.

III. APPROACH

In this paper we present a three stage range only localization process with no knowledge of prior feature locations; here, a handful of observation information is fused together to determine feature locations. Importantly, one of the most vital issues at hand when dealing with range only data is the aspect of ambiguity, i.e. a single range data alone is not enough to derive feature position estimate.

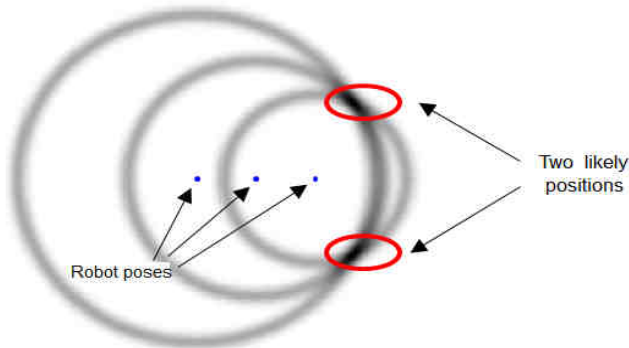


Fig. 1. Range measurement made from three collinear points has two likely positions.

More importantly, as illustrated in figure 1 above, a robot making range measurements from two or more collinear positions to a feature in the environment is faced with a dilemma of selecting the actual position of the beacon from the two equally likely positions. In this case, the orientation of the robot is not important. It is however fundamental that range measurements made are allied to the cumulative robot’s encoder reading at a time of measurements. If the predicted positions from the encoder and range measurements are linked, then range measurements can be described as circles in a plane, with a centre at robot position and radii equal to measured ranges.

I. Outlier Rejection

Unlike most outlier rejection methods [15 and 16], spectral graph partitioning outlier rejection method reported in [11], does not require prior knowledge of data classed as outliers. The method automatically classifies measurements data based on consistent and inconsistent data. Inlier measurements are shown by circles which tend to be highly consistent, whereas outliers are represented by random intersection.

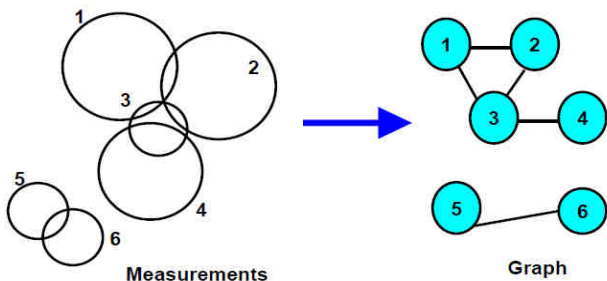


Fig. 2. Measurement connectivity and nodal graphical representation

As illustrated by figure 2 above, outlier rejection by Graphical partitioning method is posed as two sets class of outliers and inliers. Thus, nodes 1-4 are highly connected (consistent) whereas nodes 5-6 though connected are less likely to be classed as inliers. Importantly, the relative position of a node

from others has no significance in graphical representation but its connectivity to other nodes in its vicinity is more important. Applied on real range data from odyssey III [11], the spectral graphical partitioning algorithm ‘cleans’ the data shown in figure 3 by treating the unconnected nodes and/or random connections as outliers. The resulting solution after rejection method is a usable highly connected data shown in figure 4.

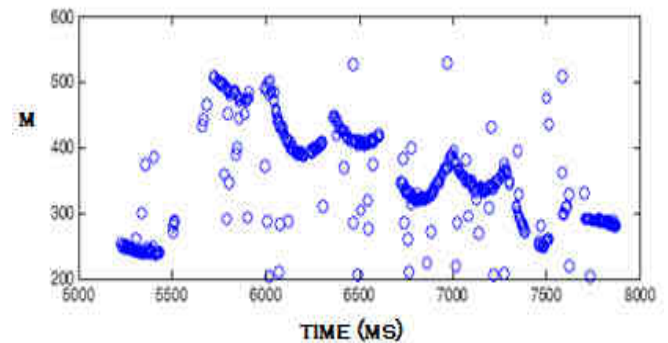


Fig. 3. Data sets with outliers

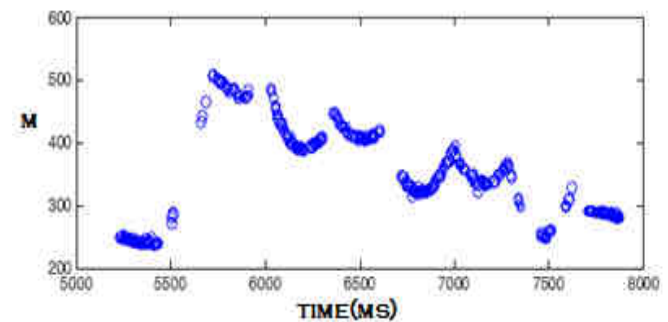


Fig. 4. Range data sets showing inliers (without outliers)

II. Particle Swarm Optimization

Inlier data shown in figure 4 above represent data information recorded at different time stamps from a beacon placed approximately between 200m and 500m. Due to noise and ambiguous nature of range only data, two equally likely possible solutions are obtained. To find a highly likely solution, Particle Swarm Intelligence is used to find the disparity between the two solutions. PSO was first developed by [17] as a stochastic optimization technique to mimic the social behaviour of bird flocking and fish schooling. Like most evolutionary optimization algorithms, PSO is also a population based search technique modelled on swarm intelligence. Initially, particle positions are randomly generated and then allowed to fly through the search space based on an objective function. Each particle in the population represents a possible solution to the optimization problem, and their coordinates are based on velocity and position vector. Furthermore, each particle in the population shares information with others to optimize the search experience. At each time step, a particle computes and remembers its best experience as well as the best positions attained by other particles in its vicinity. The best position visited so far by the current particle is called local best (Pbest) whereas the best particle in the population is called global best (Gbest). Consequently, the position of each particle in the search space is influenced by all particle members because of information sharing.

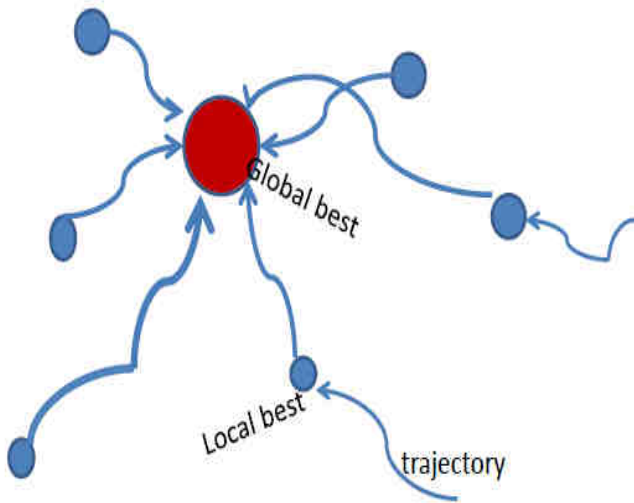


Fig. 5. Illustration of PSO technique

As illustrated by the figure 5 above, each particle at each time step is accelerated towards its local best and global best to archive optimum search solution of the population. Each particle in the swarm is represented by the following parameters:

X_i : The current position of the particle i .

V_i : The current velocity of the particle i .

P_i : The best position of particle i attained so far, whereas P_g is the best global position attained by the whole swarm so far. At each iteration, both velocity and position vector for each particle are updated using the following equations

$$V_i = w_i \cdot V_i + c_1 \cdot r_1 \cdot (P_i - X_i) + c_2 \cdot r_2 \cdot (P_g - X_i) \quad (1)$$

$$X_i = X_i + V_i \quad (2)$$

Where: c_1 and c_2 are stochastic acceleration cognitive components, r_1 and r_2 are two random real random distribution numbers in the range $U [0, 1]$. w is an inertial weight coefficient defined between 1 and ≈ 0 ; it plays a critical role in facilitating a balance in the exploration and exploitation of the search space. During each generation (iteration), the inertia reduces dramatically from a unit to about zero according to the following formula:

$$w_i = w_{\max} - \frac{w_{\max} - w_{\min}}{it_{\max}} \cdot it \quad (3)$$

From equation 3 above, it and it_{\max} indicates the current iteration number and maximum number of iterations respectively, whereas w_{\max} and w_{\min} parameters define the bounds of the inertial weight.

III. Cluster assignments

Passing inlier data through k-means clustering algorithm which uses chi-distance measure [19], consistent data measurements will have two dominant clusters as shown by Figure 6 below as well as the centroids of the two clusters.

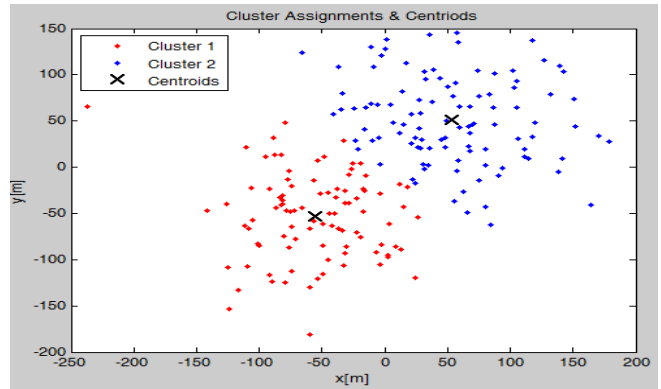


Fig. 6. Clusters and Cluster centroids

Using a circle of radius 30 m as an objective function for the PSO, the number of particles flying into the circle can be established at each iteration. Initially, particles occupy the position of particles in the two clusters as illustrated in in figure 6 above. A likely cluster has a high level of consistency with particles that are closely clustered which turns to converge quickly to the mean (centroid) when applied to the PSO algorithm. Thus in the end, a probably cluster will have a high percentage of particles within the circle after a few iterations, as shown in the figure 7 below.

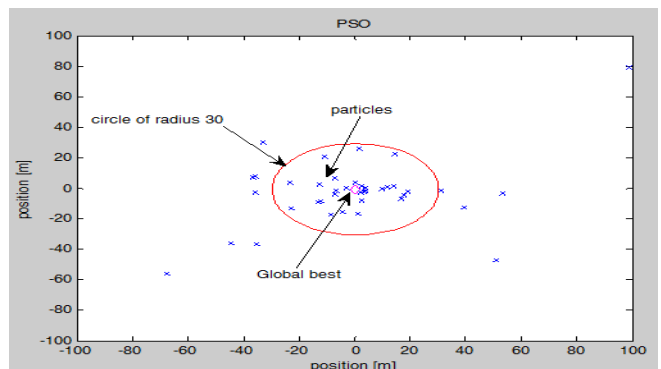


Fig 7. Fully connected topology defined with a circle of radius $r = 30m$.

In particle swarm optimization systems, particles are connected to each other in a number of neighbourhood topology, such local best topology, ring topologies, and star topology [18]. The fully connected topology (star) illustrated by figure 7 above is preferred in this paper due to its fast convergence. In this neighbour topology, each particle uses its past experiences in terms of personal best (P_i) as well as the position of the best particle (P_g) from the entire swarm.

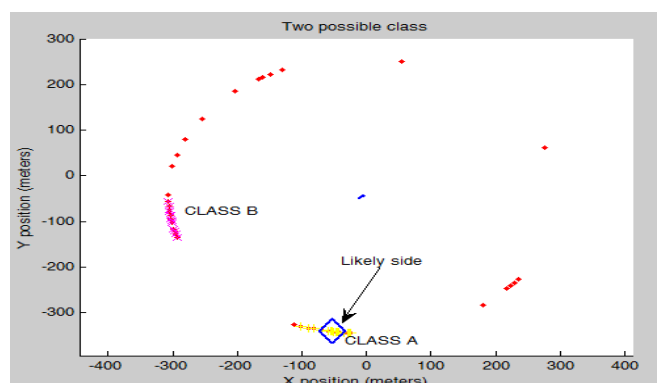


Fig. 8. Range data showing two possibly likely positions (CLASS A is likely to contain the true position)

Using PSO, a highly likely beacon location is identified (blue diamond) as shown in figure 8 above. This means that the mean of data in class A is closer to the actual position of the beacon. The red squares also illustrate places of consistent intersections, but might be as a result of noise.

IV. Area under the graph

As already stated, it is almost impossible to disambiguate the true beacon position if the vehicle is travelling on a collinear path.

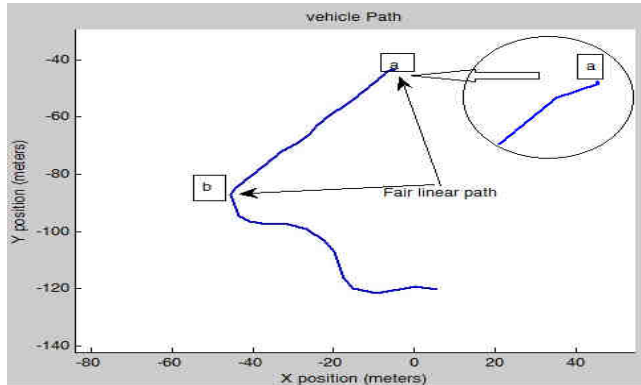


Fig. 9. Vehicle path

The path shown in figure 9 above is marked at point *a* and *b*, from point *a*, the vehicle experience slight turns and the path straightens up around the middle section until point *b*. Thus, as long as a vehicle is travelling in straight line, determining the location of a beacon is almost impossible. This is why, in a paper presented by [11], a 2:1 thresholding method is used to initialize a beacon. Admittedly, it is reported in the paper that a delayed initialization of a beacon may lead to localization system divergence. In this paper however, an inlier data set is passed through PSO algorithm which classes the data into two clusters, i.e. CLASS A and CLASS B, as shown in figure 8. Each class is then subjected to Gaussian distribution statistics to calculate the area under the graph bounded by $\pm 3\sigma$. As a disambiguating measure, a class with area magnitude of 0.65 m² to 1 m² was selected as a class that is likely to contain beacon location. Another conditions used to validate the existence of beacon in a certain class is the difference between areas, in this paper, area difference of about 0.5 m² were used.

Table 1. Areas under the graph of data of both CLASS A and B and their differences

Data sets	Area under graph (CLASS A)	Area under graph (CLASS B)	Area CLASS A – Area CLASS B	CLASS A (Mean)	CLASS B (Mean)
1	0.997140	0.000000	0.99714	-53.5834	-301.3801
2	0.996989	0.000711	0.9963	-84.3115	-291.1527
3	0.996497	0.000015	0.9965	-94.4843	-289.6868
4	0.996535	0.463268	0.5333	-98.2382	-289.6868
5	0.996391	0.584870	0.4115	-103.4094	-281.9057
6	0.996939	0.790759	0.2062	-137.0558	-280.7441
7	0.996621	0.436655	0.5600	-142.3097	-283.4934

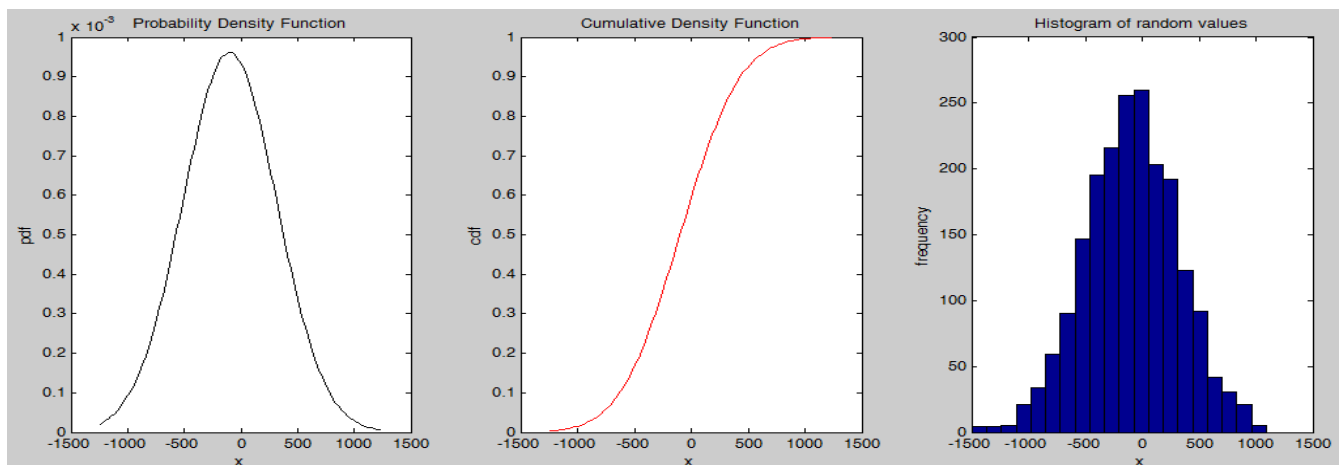


Fig. 10. Pdf, Cumulative Density Function and Histogram of random values for Class A using data sets 4.

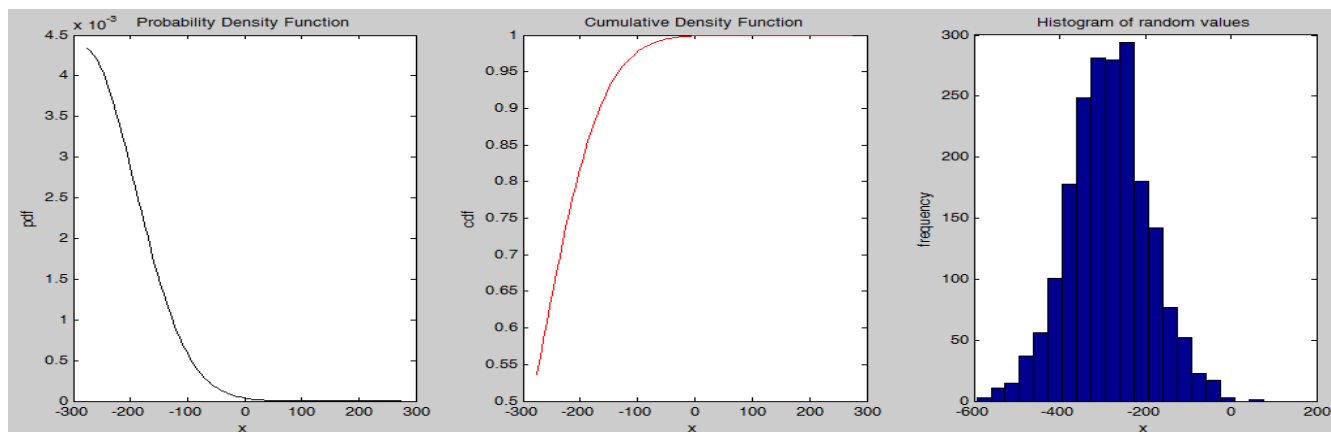


Fig. 11.Pdf, Cumulative Density Function and Histogram of random values for Class B using data sets 4.

As shown in table 1 above, data sets 1 to 6 has decreasing area differences from about 1 m² to 0.2 m². This is expected because from point *a*, the path is slightly wiggly but then it straightens up close to point *b*. At this point, both classes are highly likely, hence the area under the graph for both classes are almost equal. After point *b*, the area of CLASS B reduces again because the path curves, hence the difference between the areas increase. Using data set 4 as indicated in table 1 above, the mean of the probability distribution is – 98.24 for CLASS A data while the area under the Gaussian graph is almost 1 m². Correspondingly, CLASS B data has a mean at -289.67 and an area of 0.4633 m², defined within $\pm 3\sigma$ bounds. Figure 10 and 11 above shows the pictorial representation of the statistics of CLASS A and CLASS B for data set 4.

IV. CONCLUSION AND RESULTS

Using Range only data for localization presents a challenging problem because a single measurement does not contain enough information to compute beacon position estimates. Furthermore, due to the nature of measurements involved, range data is known contain outliers; requiring the use of pre-filter before further applications. The results presented in this paper shows that the ability to quickly disambiguate possible beacon location or beacon initialization is crucial for localization systems. The unobservable nature of the data involved means more data is fused to initialize a beacon leading to delayed system update hence system divergence. Improving the initialization process of beacons into the ‘map’ directly translate to improved localization system. The results reported in this paper use a two stage process to disambiguate range data using few range measurements. The PSO results give a possible likely cluster while the area under the graph confirms a class which is highly probable. Since both methods point to the same cluster, i.e. the probable class is similar to the cluster identified by PSO; initialised beacon(s) in the ‘map’ are then used to update the localization system. If system update is done frequently, localization system turns to converge leading to improved navigation system.

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Molaletsa Namoshe has BSc of Science part I from the University of Botswana (2001), MEng Control System Engineering from the University of Sheffield (UK), (2005) and Doctor of Technology from Tshwane University of Technology, Pretoria, South Africa (2011). During his DTech study with Tshwane University of Technology, he was also working as a Candidate Researcher at The Council for Scientific &

Industrial Research (CSIR) in Pretoria, South Africa, where I was part of the Mechatronics & Micro-Manufacturing Research Group whose main research focus in Autonomous Robotic Systems. Mechatronics systems, cooperative Simultaneous Localization and Mapping (SALM) mobile Robotics, distributed systems, metrology, measurements standards, control systems, applied control, calibration and instrumentation. Currently he has developed interest in Particle Swarm Intelligence, Finite Element Modelling and Artificial Intelligence. He has published two book chapters, and 5 conference papers. He was working for ABM university college as an electrical engineering Lecturer from 2011-2012 and he is currently working at Botswana International University of Science and Technology, teaching Engineering graphics, workshop technology and Electrical modules. He is currently supervising 7 students handling topics from Optimization of agricultural machines, Design and optimization of machinery for Botswana's veldt resources such as Morama and Morula nuts, EKF, PID, Fuzzy logic parameter tuning using Particle swarm optimization.



Oduetse Matsebe I completed an M.Eng in Electronic, Control & Systems Engineering from The University of Sheffield in the United Kingdom and a D.Tech in Mechatronics from Tshwane University of Technology specializing in the fields of Robotics & Automation. Currently, I work as a Lecturer in the College of Engineering & Technology at The

Botswana International University of Science & Technology where I teach courses in Mechatronics, Control & Instrumentation, and Electrical & Electronic Engineering. I also worked as a Candidate Researcher at The Council for Scientific & Industrial Research (CSIR) in Pretoria, South Africa, where I was part of the Mechatronics & Micro-Manufacturing Research Group whose main research focus in Autonomous Robotic Systems. This research group conducted a complex and multi-disciplinary research that covers engineering disciplines such areas of control systems, electronics, electrical, software, mechanical and manufacturing. This is normally referred to as Mechatronics Engineering. Again, I worked as a Part-Time Lecturer at Tshwane University of Technology in Pretoria, South Africa where I taught courses in Industrial Engineering. I also worked as Lecturer at ABM University College in Botswana teaching courses in Electrical & Electronic Engineering. My research interests include robotics, automation, energy and Reconfigurable Manufacturing Systems.



Ngatho S. Tiale has Bachelor of Science Mechanical Engineering from university of Kwazulu Natal, Durban, South Africa, Master of Science Mechanical Engineering and Ph. D. mechanical Engineering from (UKZN), He has Mater of Business Administration from University of Pretoria, Pretoria, South Africa. Lecturer, His experience include working as a lecturer for Massey University, January 2002 – December

2004, Senior lecturer, University of Pretoria, January 2005 – December 2005, Research Group Leader, Competence Area Manager and Principal researcher, CSIR, January 2006 – December 2012, Research Engineer in Robotics and Automation, Anglo American PLC, July 2012 – 2014, Johannesburg Area, South Africa, Executive Manager: Processes and Automation, Transnet, Johannesburg Area, South Africa December 2014 – Present. He has published over 80 peer reviewed work around the world.