

RANGE-BASED NETWORK FORMATION TO SUPPORT GEOREFERENCING OF MAPPING SWARM PLATFORMS

Ladai, A.^{1,*}, C. Toth²

¹Department of Manufacturing and Civil Engineering, Norwegian University of Science and Technology (NTNU) in Gjøvik, Teknologiveien 22, 2815 Gjøvik, Norway - andras.ladai@ntnu.no

²Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, toth.2@osu.edu

KEY WORDS: Geodetic Networks, Point Spatial Distributions, Swarm Mapping, Adjustment

ABSTRACT:

Mapping platforms jointly operating in a formation are increasingly used to improve the efficiency of geospatial data acquisition recently. For example, UAS swarm mapping is gaining market share or robot platform are used for indoor mapping. These platforms are typically equipped with imaging and navigation sensors as well as have various communication capabilities. Until now, the platforms are individually navigated and georeferenced. Since the platforms are typically sharing a small area, and thus, they are within their sensing range; for example, they can see and thus track each other in optical or lidar imagery. Furthermore, new communication technologies have started to provide ranging information between communication points. Using the ranges between platforms makes it feasible to create a local geodetic network defined by the platforms. The geometric strength of the network then can be exploited to support platform georeferencing. In this study, the network formation based on ranges is investigated. Initial experiences are reported on the impact of the size of the network, the spatial distribution of the network nodes and the number of available ranges.

1. INTRODUCTION

Mapping sensors are increasingly deployed on multiple platforms to increase productivity and/or to provide different observations of an area. The use of UAS in mapping and delivery services has been steadily rising, so for safety and other reason, the platforms must be efficiently positioned and navigated. Similarly, robots are supporting indoor mapping at a growing rate, and pose less challenges for safety.

Remote sensing platforms deployed on the ground and in air form a network that can be observed by a variety of sensors, such as camera, RF signals, LiDAR, etc. (Toth and Jozkow, 2015). The most typical measurements are ranges and angular observations. When sufficient data are available, the network, the relative positions of the platforms can be estimated. The network can provide relative positioning of the platforms that can be used to check the quality of the individual platform navigation solutions and also to improve the navigation solutions of nodes that may lack navigation sensor data and thus may have compromised or no navigation solution at all.

Collaborative navigation or cooperative positioning is a recent concept that is based on data sharing between navigation platforms, such as a mapping swarm (Masiero et al., 2021). If platforms share their navigation sensor data, such as GNSS and IMU as well as range and angular observations between platforms, then a central navigation filter can compute an optimal solution for the entire swarm. The method is somewhat similar to aerial triangulation where the number of ground controls can be reduced, which is the equivalent of having a few nodes with good GNSS data in the swarm that can be propagated to other nodes through the network. Obviously, the performance dependence on the ranging accuracy and some other conditions.

The long-term objectives of this effort are: (1) what is theoretical foundation for the spatial distribution of points in terms of the impact of network or object space reconstructing, and (2) the practical goal is to support collaborative navigation of UAS

swarm mapping. In this study, the feasibility of using free network adjustment is investigated to support the georeferencing and navigation of a group of platforms operating in close vicinity. So far, we are only considering the 2D case and using range data.

2. DATA ACQUISITION

When clear LOS is available, obtaining range and angular data (AoA) is generally feasible. But when obstacles exist in the space where the platforms are deployed, there may be not enough information to estimate the network. Therefore, we selected a generally open area with a few buildings where reference points could be easily established and surveyed at high accuracy.

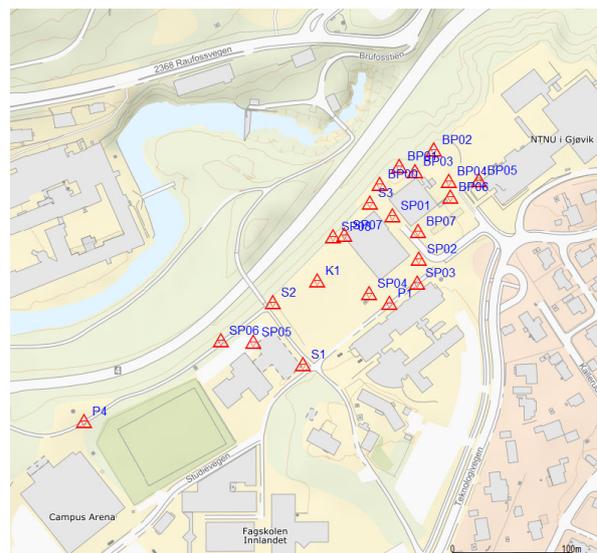


Figure 1. Network at NTNU Gjøvik campus

* Corresponding author

We have set up a test area on the Gjøvik campus of NTNU where ground controls were deployed and accurately surveyed to support both simulations and UAS flight experiments, see Fig. 1. The campus represents a mixed environment of widely empty spaces and corridors between buildings, making it ideal for investigating the behavior of an UAS swarm flying around buildings in an urban area. A static network of 36 points was established using a Leica MS60 multistation, from which 22 were used in our investigation. The triangulated geometry, derived from numerous angular and distance measurements at each station ensured mm level final accuracy; clearly, this is better than what is required for highly accurate platform georeferencing. This static network provides an excellent basis for simulations, and the permanently marked points (nails in asphalt and pillars) will provide ground control for further UAS test flight-based investigations.

Network Simulation

Horizontal range observations were simulated between each point pairs, and noise was added to each observation based on their estimated quality. First, the quality of the range data was estimated from the performance of a Leica M60 multistation's distance measurement. Note that the centering reliability was also estimated at each point by assuming that all the observations from a point were done simultaneously, so the same centering accuracy impacted all the sets of observations at one point. Based on the estimated standard deviations, a normal distribution-based random generator assigned the noise to each observation. The weights of observations were also derived from those estimated standard deviation values. This error characterized datasets were used for testing the implementation of the network computation tools and then the initial tests with various network configurations.

3. NETWORK FORMATION

For the 2D network case, there are two methods tested in this study. The first one, Method I is based on a conventional incremental network formation, while the second one, Method II is a single one-step network formation. Both methods can work without knowing any absolute coordinates of any nodes; i.e., no anchor node information is available. While Method I is proven method, it was designed for static networks, and computationally somewhat strict, so it is less applicable for an application when the network is constantly changing, such as flying drones, and thus, a fast solution is needed. Fig. 2 shows a typical network formed by 10 nodes (n) with all the possible ranges between nodes; i.e., 45 based on $\binom{n}{2}$.

Method I

The traditional geodetic solution requires a priori estimates of X and Y coordinates, as otherwise the adjustment may not converge. Assuming good initial values, the weighted least squares method will provide the optimal distribution of residuals among the unknown parameters (Ghilani, 2017). While an unambiguous solution based only on range observation requires three points with known X and Y coordinates, solutions with only two anchor points were also tested, with some extra attention. When a drone network starts, there may be no reliable initial coordinates, in which case Method I may not work at all. Note that the network is a sample of the swarm motion at a certain epoch. As the swarm operates, there are position estimates available for the nodes, and thus Method I can deliver a network solution for the given epoch. Then, the solution can be analyzed

for gross errors, etc., and a clean network solution can be used to update the position estimates for the entire network.

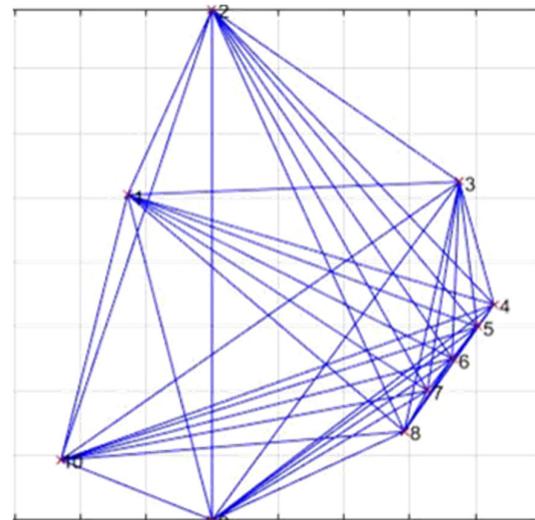


Figure 2. Network of 10 nodes with all the ranges

Method II

This approach basically tries to form a network only from range measurements; ideally, all the ranges between nodes would be available, but in practice, only a subset can be observed. First a local coordinate system should be setup, which is based on two nodes defined by the largest range. In our implementation, one of the this point is considered as the origin and then second defines the Y axis; in other words, nodes have the coordinates of (0, 0) and (0, range_{\max}), respectively, see Fig. 2. Next, a Gauss-Markov Model with constraints is executed, (Snow and Schaffrin, 2021). The adjustment is not guaranteed to provide a unique solution or solution at all, depending on several factors. There are additional tools which offer more complexity to address these challenging networks if needed. One obvious problem with the 2-point defined local coordinate system is that there could be two solutions, the correct and the mirrored one; assuming that the solution is close to horizontal in the mapping frame. Obviously, in 3D sense there is only one solution.

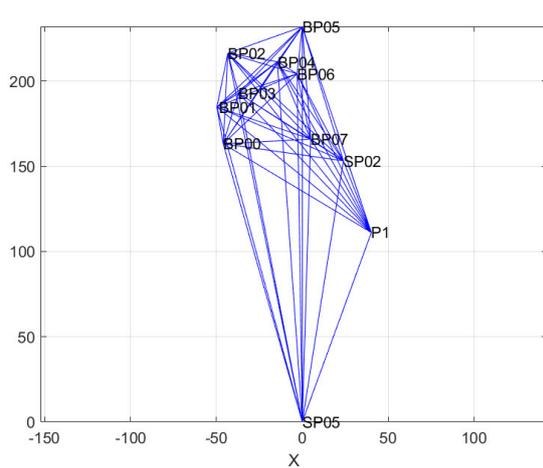
Both methods have been implemented in Matlab and formed the tools to test various network configurations. During the investigations, the solution provided by Method I was considered as a reference, and thus, served to validate Method II. Besides the direct comparison of the two solutions, the quality of the adjustment of different configurations was assessed by analyzing the standard deviation of the adjusted X and Y coordinates and the related error ellipses.

4. PERFORMANCE EVALUATION

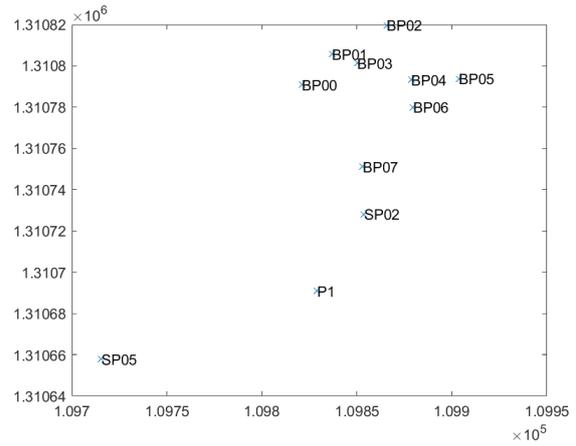
Various parameter combinations are tested, including

- The number of network nodes
- Different network node distributions
- What is the minimum number of ranges available to form a network?

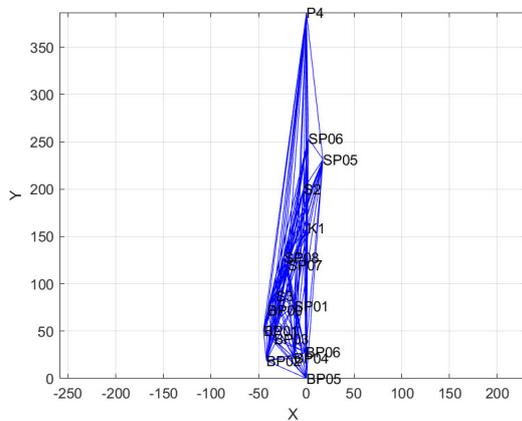
The initial results of the first two objectives are discussed here. Fig. 3 shows typical network adjustment results of Method II.



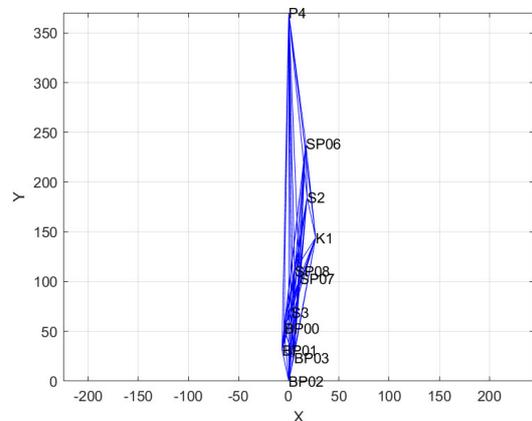
(a) A typical case for 11 points with 7 iterations



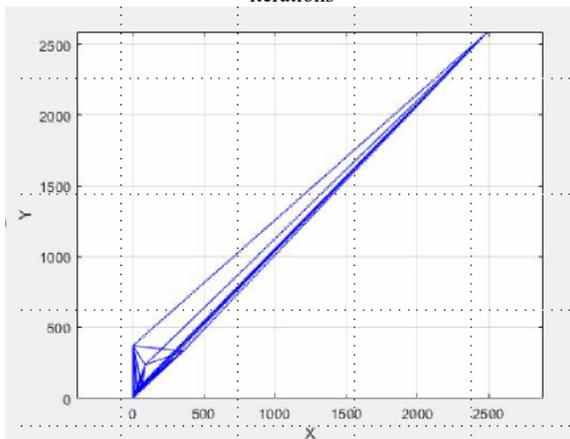
(b) Using ground coordinates of two nodes, the network is transformed (rotated) into the mapping frame



(c) A corridor point distribution case for 16 points with 17 iterations



(d) Another corridor distribution case for 11 points with 66 iterations



(e) Divergent case with 7 nodes; solution oscillates

Figure 3. Various network computations

Method II generally converges; the iteration number seems to be somewhat correlated to the spatial distribution of the points. Fig. 3a is nearly even spatial distribution with low iteration number. Fig. 3c is a less than ideal distribution, yet the iteration number is not too large. Fig. 3d shows a successful but slow convergence

case. Fig. 3e shows a small network where the solution oscillates. In general, for larger number of nodes, the failure rate slightly increases, but there are exceptions. The spatial distribution of the nodes clearly has a strong influence on the success of the network formation. This is a challenging problem.

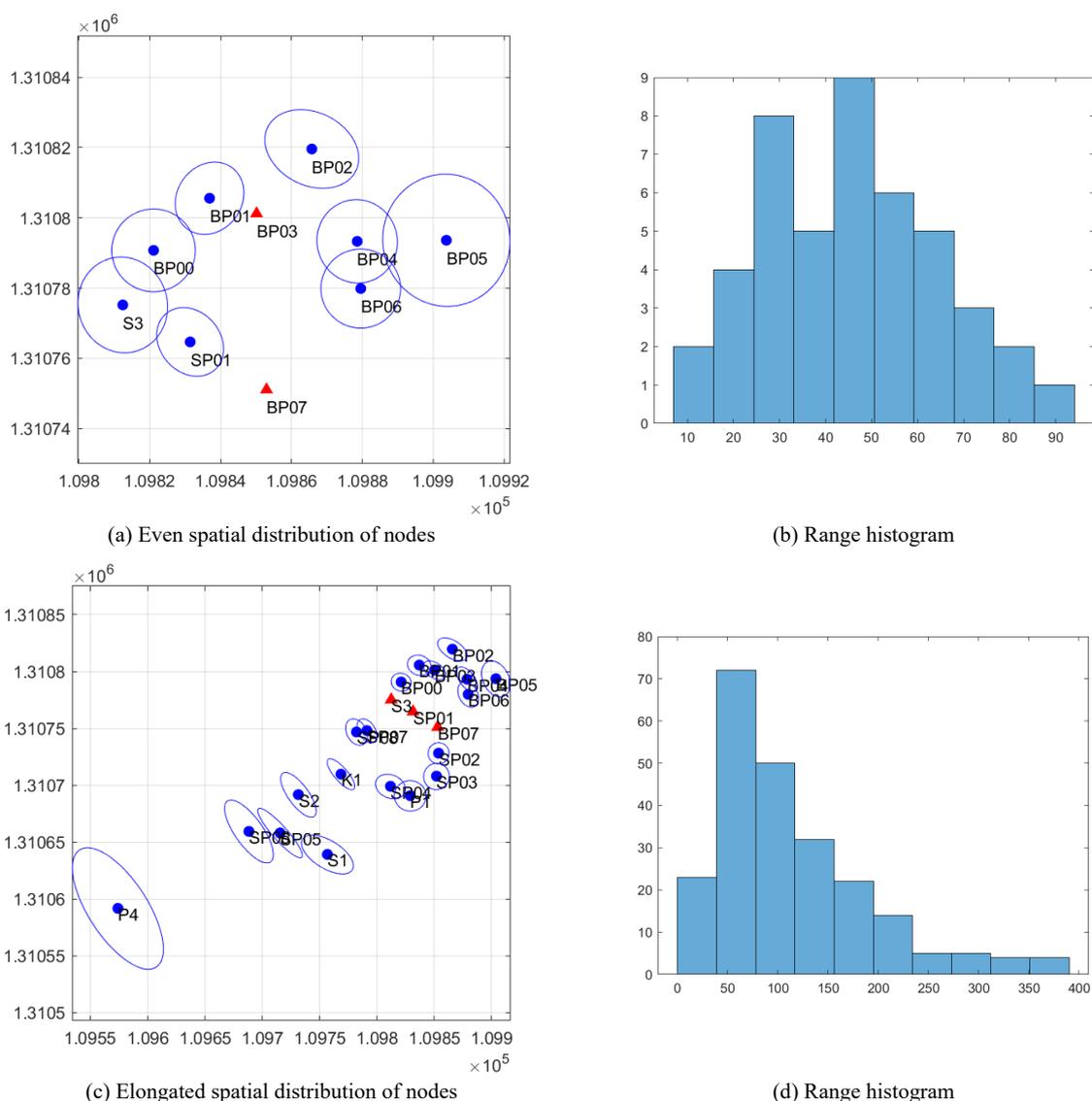


Figure 4. Relationship between spatial distribution of points and range histogram

Fig. 4 shows range histogram of two networks with very different spatial distribution of nodes. As expected, the balanced histogram in Fig. 4b indicates a likely even spatial distribution of the point. In contrast, the skewed range histogram in Fig. 4d suggest a less than ideal point distribution.

The error ellipses are also included in Figs. 4a and 4c for the cases when 2 and 3 anchor nodes were introduced. Fig. 4a demonstrates that the control information for the two nodes with ground coordinates has no real impact on the network accuracy; in other words network positions determined by Method II are not impacted with the introduction of two control points, as the base formed by the two points is comparable to the size of the network. In contrast, Fig. 4c shows a totally different case where the accuracy of the georeferenced network is noticeably impacted by the introduction of the three anchor nodes. Since they are close to each other and fall on a line, they have impact only on the closest node points and then with distance the errors grow in the lateral direction.

Fig. 5 shows additional illustration for networks absolute georeferenced based on 2 and 3 anchors; the very same local network computed by Method II is shown in the four subfigures with various anchor point selections. Since it is a corridor network point distribution, the error ellipses have larger extent in the perpendicular direction with respect to the main corridor direction, as there is only limited observation in the lateral direction.

Figs. 5a and 5c show that using anchors that are selected from the two end areas of the network provide even accuracies; as expected, point P4 has larger error ellipses, as it is extrapolated as opposed to interpolated. Adding a third anchor point in the center makes no difference, as this point fall on the line defined by the two original anchor points, see Fig. 5c.

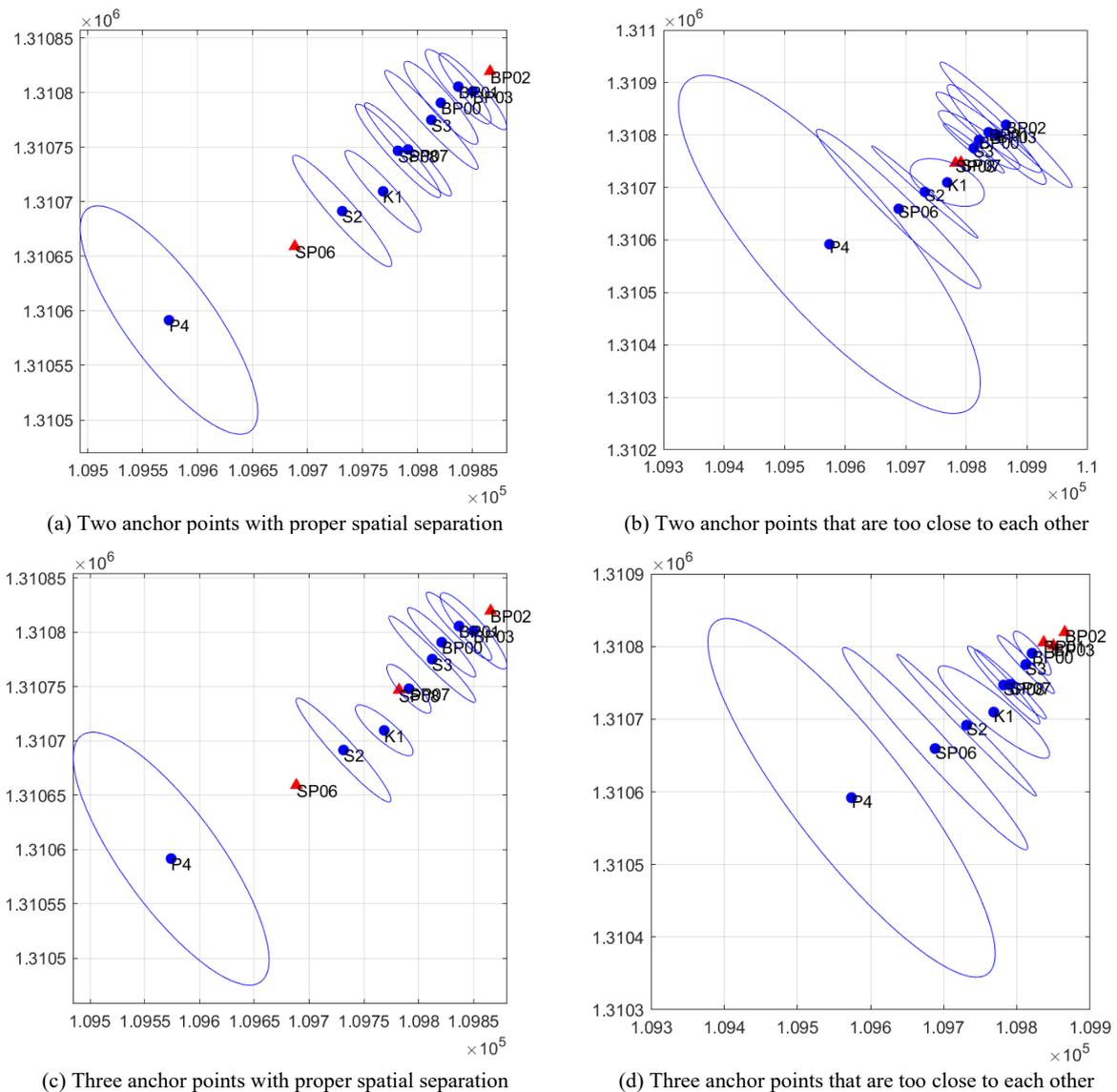


Figure 5. Impact of the spatial distribution of anchor points on a corridor distributed swarm network

Figs. 5b and 5d show the situation when the anchors are close to each with respect to spatial extent of the network points. As expected, the impact of the anchors is only noticeable on the nearby points, and then with distance the errors will grow. The location of the anchor points, whether it is at the end or the mid of the points, has no impact in general, except that the same error growth can be seen on one or both sides with respect to the location of the anchors. Similarly, to the ideal case, the number of anchors has practically no impact on the error patterns.

5. CONCLUSION

Two network adjustment methods have been investigated using a realistic network configuration for urban UAS swarm drone mapping. The classical solution served as a reference and the proposed one-step method was intended to offer a faster computation, which makes it applicable to dynamically changing

network, such as one formed by the platforms of a mapping swarm.

The preliminary results are encouraging, as the one-step method generally performed well in terms of providing a network solution based only on ranges observed between the nodes. In contrast, the traditional method always delivered the good solution, but required more execution time. The compromise between faster execution time and the fact that convergence is not guaranteed is probably acceptable in real-time applications, where the platforms have continuous navigation, so not getting an update or improvement once in a while is not causing an problem.

Future work will address the impact of varying ranging accuracy on the solution and the contribution of the spatial distribution of the nodes for successful network formation.

REFERENCES

- Masiero, A.; Toth, C.; Gabela, J.; Retscher, G.; Kealy, A.; Perakis, H.; Gikas, V.; Grejner-Brzezinska, D. (2021) Experimental Assessment of UWB and Vision-Based Car Cooperative Positioning System. *Remote Sens.* 2021, 13, 4858. <https://doi.org/10.3390/rs13234858>
- Ghilani, Ch. D. (2017) Adjustment Computations: Spatial Data Analysis, 6th Edition, 2017, ISBN: 978-1-119-38598-1
- Matlab Computer Vision Toolbox™
<https://www.mathworks.com/products/computer-vision.html>
- Sluis, B., Toth, Ch. (2021) 2-Dimensional Geometric Analysis of a Simple Free Network, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume V-4-2021, pp.147-152.
- Snow, K., Schaffrin, B. (2021) *Adjustment Computations*. Based on Courses GS 650, GS 651, & GS 762, The Ohio State University.
- Toth, C., Jozkow, G. (2015) Remote Sensing Platforms and Sensors: A Survey, *ISPRS Journal of Photogrammetry & Remote Sensing*, 115 (2016), pp. 22-36.