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Using the particle swarm optimization for geoid determination

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Abstract

Geoid determination is the modelling that enables us to determine the height of a point whose position is known. Geoid determination has made important problem of Geodesy with GPS technologies. One of the important points when determining the geoid is to select the outlier points in the data set. These points named as outlier measurements. These points are determined by the outlier measurements test. There are many different methods used in the literature to determine outlier measurements. The most widely used of these is The Least Square Method (LS). Also nowadays, very complex problems can be solved with methods such as the rapidly developing Artificial Intelligence and Machine Learning Technologies with Metaheuristic Algorithm for obtaining a close to optimum solution. One of these algorithms is Particle Swarm Optimization. In this study, the usability of the particle swarm optimization was tested to determine the outlier measurement in the geoid determination process.

1. Introduction

Metaheuristic algorithms have become popular in finding the best in recent years and are still used in many optimization problems (Canayaz, 2015). Its use in Geomatics studies has just begun.

The geoid is a gravity equipotential surface to which the elevation of a point can be conveniently referred. The computation of the geoid is based on the solution of the field equation of gravitation which describes gravitation in the small and in which the rotating frame of reference is time independent to a first order approximation (Zhang, 1997). The solution is adjustment to increase the accuracy in geoid determination. In the problem, the measurements, which is much than the required number cause discrepancy between measurements and in this case, the solution is not unique. An objective function is made for the unique solution. It is seen that usually the objective functions are formed by minimization of corrections or a function of corrections and the two methods come forward (Sisman, 2010). The most used methods are The Least Square Method (LS) and The Least Absolute Value Method (LAV).

In this study a data set consisting of 312 points concern to a section of the land at Ondokuz Mayis University in Samsun was used. Firstly, the outlier measurements in the data set were removed. Then the same data set was tested on one of the metaheuristic algorithms, Particle Swarm Optimization (PSO). The results of both methods were examined and compared.

2. Method

2.1. Metaheuristic algorithm

Metaheuristic algorithms appear as comprehensive algorithms that are above heuristics and decide which method to use in solving problems. Metaheuristics have developed dramatically. (Osman & Kelly, 1997). In order for Metaheuristic algorithms to be usable, they must meet certain criteria. At the beginning of these criteria are the closeness of the solutions they found to the optimum value and the time they spent in obtaining these solutions. The fact that the algorithms are coded in a way that can be understood by everyone and provides ease of analysis is also an important factor in the selection of algorithms (Canayaz, 2015). There are many different metaheuristic algorithms in the literature. These are; Firefly Algorithm, Genetic Algorithm (Banzhaf, Nordin, Keller, & Francone, 1998), Shuffled Frog Leaping Algorithm (Eusuff, Lansey, & Pasha, 2006), Particle Swarm optimization (Lazinica, 2009), Ant Colony Optimization(Maniezzo, Gambardella, & Luigi, 2004) etc.

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2.1.1. Particle swarm optimization

Particle swarm optimization (PSO) algorithm is a stochastic optimization technique based on swarm, which was a proposed by Eberhart and Kennedy (Eberhart & Kennedy, 1995). PSO algorithm simulates animal's social behavior, including insects, herds, birds and fishes. These swarms conform a cooperative way to find food and each member in the swarms keeps changing the search pattern according to the learning experiences of its own and other members (Wang, Tan, & Liu, 2018).

Each individual in the particle swarm is composed of three D-dimensional vectors, where D is the dimensionality of the search space. These are the current position x_i , the previous best position p_i , and the velocity v_i .

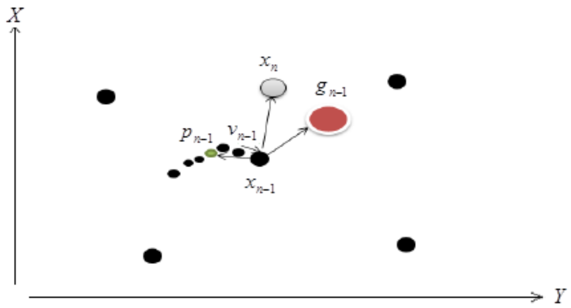

Figure 1. PSO mechanism (Gökçe, Durusu, & Ridvan, 2022)

The current position x_i can be considered as a set of coordinates describing a point in space. On each iteration of the algorithm, the current position is evaluated as a problem solution. If that position is better than any that has been found so far, then the coordinates are stored in the second vector, p_i . The value of the best function result so far is stored in a variable that can be called $pbest_i$ (for "previous best"), for comparison on later iterations. The objective, of course, is to keep finding better positions and updating p_i and $pbest_i$. New points are chosen by adding v_i coordinates to x_i , and the algorithm operates by adjusting v_i , which can effectively be seen as a step size.

The particle swarm is more than just a collection of particles. A particle by itself has almost no power to solve any problem; progress occurs only when the particles interact (Poli, Kennedy, & Blackwell, 2007).

Suppose there are n particles consisting of D parameters. So, population particle matrix equation is;

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1D} \\ x_{21} & x_{22} & \dots & x_{2D} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{nD} \end{bmatrix}$$

The position ($pbest_i$) of the i 'th particle the best fitness value;

$$pbest_i = [P_{i1}, P_{i2}, \dots, P_{iD}]$$

The other best value is the coordinates that provide the best solution obtained by all particles in the population so far ($gbest_i$) .

$$gbest_i = [P_1, P_2, \dots, P_D]$$

i.th particle correction;

$$v_i = [v_{i1}, v_{i2}, \dots, v_{iD}]$$

After finding the two best values, particle velocities and positions are updated according to the equations given below(ÇEVİK & KOÇER, 2013) .

$$v_i^{k+1} = v_i^k + c_1 * rand_1^k (pbest_i^k - x_i^k) + c_2 * rand_2^k (gbest^k - x_i^{k+1})$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

2.2. Geoid determination and GNSS levelling

The geoid is a complex surface and formed by the combination of the points have got zero potential value. The geoid determination is the most important problem in the earth. Because the geoid does not represent a regular shape. Local geoid determination studies aim was to determine a local geoid using the geoid determination methods for example Polynomial Interpolation Method (Akar, Konakoğlu, & Akar, 2022).

Development of geoid modelling is based on geodetic, gravimetric and astrogeodetic techniques. In order to define a high precision geoid, GNSS levelling, one of the geodetic techniques, can be employed. It involves the transformation of GNSS-derived ellipsoidal height (h) into the orthometric height (H). Instead of levelling, orthometric heights can be calculated by using well-defined geoid models. These geoid models enable us to compute the geoid height (N), which is the difference between ellipsoidal and orthometric height values ($N = h - H$) (Albayrak, Özlüdemir, Aref, & Halicioglu, 2020).

The polynomial technique is based on the determination of polynomial surface. The surface used to determine the geoid is generally expressed in high degree polynomials with two variables (Kirici & Sisman, 2017). The orthogonal polynomials can be represented are as follow;

$$N(x, y) = \sum_{i=0}^{m} \sum_{j=0}^{k} a_{ij} x^i y^i$$

If the number of measures is greater than the unknown number in a problem, adjustment calculation is made for a univocal solution

(Montgomery, Peck, & Vining, 2021). Adjustment is a means of obtaining unique values for the unknown parameters to be determined when there are more observations than actually needed; statistical properties may be determined as by products (Ogundare, 2018). A few methods have been developed to adjustment calculation. One of these methods is the LS method.

2.2.1. The Least Square Method

The least squares method (LS) explained by Carl Friedrich Gauss in 1795 and Legendre in 1805. This method is used in many different applications (Sisman, 2014). Unknown parameters calculated with the following equation in this method.

$$\underline{X} = \left(\underline{A}^T \underline{Q}_{\ell\ell}^{-1} \underline{A}\right)^{-1} \underline{A}^T \underline{Q}_{\ell\ell}^{-1} \underline{\ell}$$

Root mean square error (RMSE);

$$m_0 = \pm\sqrt{\frac{\underline{V}^T \underline{PV}}{f}} \quad ; f = n - u$$

The measurement errors of the LS method influence the residual of other calculations. Thus, this correction value may not always be due to an error in the measurement. This situation is called the spread and storage effect of LS method. Different solution methods can be conducted for the analysis of spread and storage method.

2.3. Case study

In this study, a part of the land relate to Ondokuz Mayıs University in Samsun was used as the study area (Figure 2).

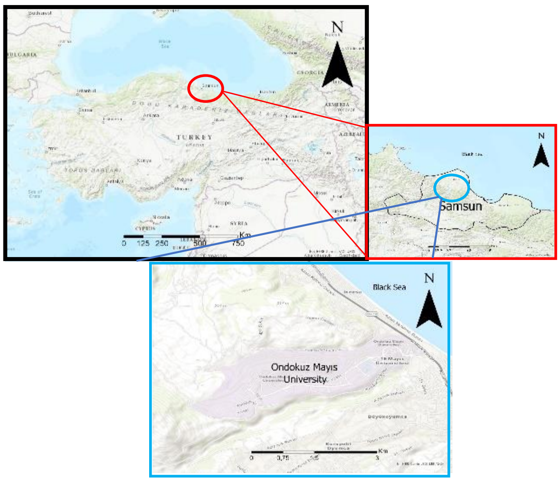

Figure 2. Study area

Data set consist of 312 points. The distribution of points with known x, y and h values is shown in Figure 3.

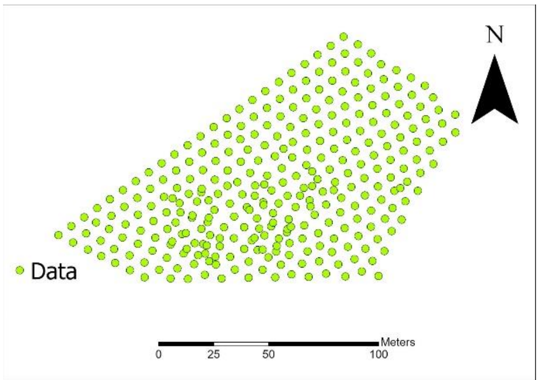

Figure 3. Data set

First, the surface model is created using the 2nd degree polynomial formula according to LS. Then, outlier points were determined depending on this method. Finally, one of the metaheuristic algorithms, PSO, was tried to determine the outlier measurement.

3. Results

LS method determines 51 of 312 points as an outlier. This means that the 51 points do not belong to the surface and the surface belongs 261 points. Figure 4 shows the distribution of the outliers which are found by the LS method.

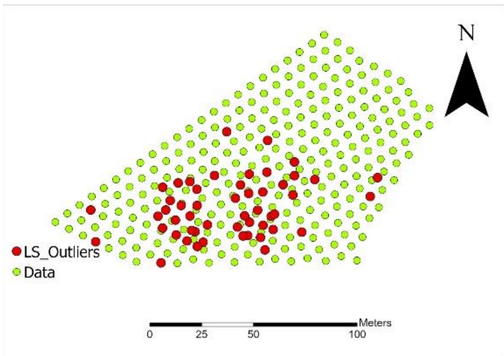

Figure 4. Outlier points of the LS Method

PSO was applied to the data set and 41 of 312 points were determined as an outlier with this method. According to the PSO, the surface consists of 271 compatible points (Figure 5).

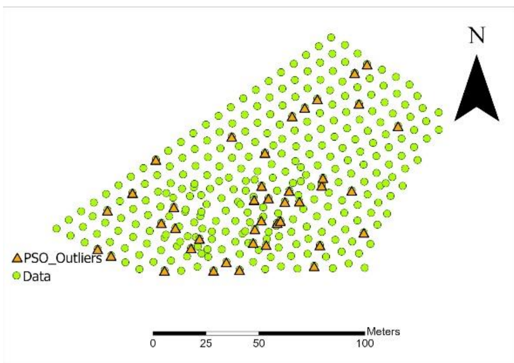

Figure 5. Outlier points of the PSO

4. Discussion

LS method was determined as an outlier in 51 points. PSO determined 41 points. When the points found in common by both methods are observed, it is seen that 16 points are common. Common points found by the two methods are shown in Figure 6.

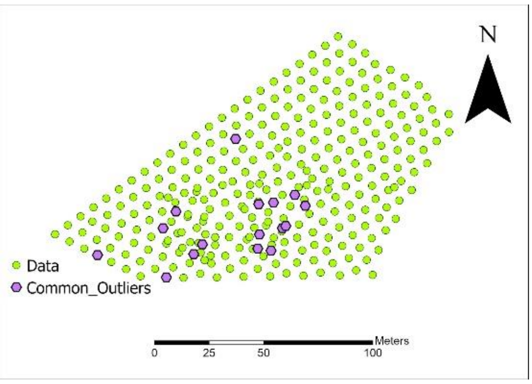

Figure 6. Common points

5. Conclusion

When the intersection points are examined, it is seen that they cover each other at the rate of 32%. This rate shows us that the use of PSO in geoid detection is limited. When the points that both methods find common are examined, it is seen that there is a density in the middle parts of the study area. According to the land structure of the study area, it is seen that the middle parts are rugged and wooded. As a result, it is understood that PSO gives more accurate results, especially in rough terrain. Metaheuristic algorithms have entered our literature as an optimization method in recent years. However, its use in geomatics engineering is not common yet. In this study, the usability of the PSO in geoid determination was tested. The study can be continued by trying different metaheuristic algorithms.

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