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Report

The Assessment of using an Intelligent Algorithm for the Interpolation of Elevation in the DTM Generation

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Summary: Several methods exist for the interpolation of digital terrain models (DTM), which have different characteristics depending on environmental conditions and input data. In this paper, the artificial intelligent (AI) techniques such as genetic algorithms (GA) and artificial neural networks (ANN) are used on the samples to optimise the interpolation methods and production of digital elevation models (DEM). The results obtained from applying GA and ANN are compared with typical methods of interpolation for the creation of elevations such as Kriging. The results show that AI methods have a high potential in the interpolation of elevations. The use of artificial networks algorithms for the interpolation and optimisation based on the quartic polynomial and inverse distance weighting (IDW) led to high precision elevations.

Zusammenfassung: *Verwendung von Methoden der künstlichen Intelligenz zur Ableitung von Höhenmodellen.* Für die Interpolation von Höhenmodellen gibt es viele Methoden. In diesem Artikel werden Methoden der künstlichen Intelligenz (artificial intelligence, AI) zur Optimierung von digitalen Höhenmodellen vorgestellt. Dazu gehören Genetische Algorithmen (GA) und künstliche neuronale Netze (ANN). Die mit diesen Methoden erzielten Ergebnisse werden bisherigen Verfahren gegenübergestellt, unter anderem dem Kriging. Im Ergebnis zeigt sich, dass die künstliche Intelligenz große Möglichkeiten bietet. Besonders die Quartic Polygone und die "inverse distance weighting"-Methode könnten für die Ableitung von genauen Höhenmodellen verwendet werden.

1 Introduction

Three-dimensional modelling of the Earth is one of the most important tools in various fields of geology, meteorology, civil engineering, environmental engineering, and numerous engineering projects, and it has many applications in geographic information systems (GIS) (Petrie & Kennie 1990, Florinsky 2011, de Mesnard 2013). In GIS, the terrain modelling is generally called digital terrain modelling (DTM) and is used to display topography and synthetic changes of many environmental parameters such as temperature, air pollution, etc. (Kasser & Egels 2002, Li et al. 2004). One of the most significant parameters in GIS is the topography of the Earth, which can be visualised in a 3D digital form to represent the digital elevation model (DEM) (Abdul-Rahman & Pilouk 2008). In other words, DEM continuously displays elevation changes of the Earth surface, which is directly proportional to the plane position (x,y) (Abdul-Rahman & Pilouk 2008, Chaplot et al. 2006, Miller & Laflamme 1958). Initially, 3D models were created physically from plastic, sand, clay, etc. (Li et al. 2004). Today, however, computers are used to display the Earth's continuous surfaces in a digital form (Heesom & Mahdjobi 2001).

One of the most important issues in the field of digital modelling is the generation of a DEM with high quality and precision under minimum costs. To estimate a continuous surface, due to the limited number of samples and the necessity of reproducing altitude points,

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mathematical interpolation functions are used to estimate the elevation of midpoints (Abdul-Rahman & Pilouk 2008). Interpolation methods are used to determine unknown altitudes of midpoints from the samples and as a result, the coordinated points are reproduced and the digitally formed Earths' continuous surfaces can be visualised. An interpolation is never exact. The inherent errors may propagate to a level that becomes inacceptable. Such errors transfer inaccurate assessments into the projects and cause the financial losses, and even produce life threatening results (Eyvazi et al. 2007, Mitas & Mitasova 1999). Therefore, one of the challenges in this field is finding an appropriate method for the height interpolation because in addition to the accuracy and distribution of sample points and the geomorphological characteristics of the Earth's surface, the method for the interpolation and the estimation of the average point height will affect the quality and the accuracy of the DEM (Li 1990, Li 1992a).

Numerous methods for the interpolation have been proposed (Hardy 1971, Hardy 1990, Larsson & Fornberg 2005), which show different results influenced by the environment's conditions and data input. Usually, the optimal method of interpolation depends on the root-mean-square error (RMSE) of the output. In most studies the comparison of interpolation methods and the selection of the optimal methods are used to achieve higher accuracy (Yanalak 2003, Amidror 2002, Rees 2000, Yang et al. 2004, Li & Heap 2011, Wagnera et al. 2012).

In this paper, AI techniques such as ANN and GA are examined to optimise the interpolation methods and the creation of DEM on the samples. At the end, the results of the estimated heights from the intelligent techniques and the usual methods of interpolation are compared.

2 Artificial Neural Networks

Artificial neural networks (ANN) are based either on the performance of the human brain and its functionality or actions can be interpreted according to the human conduct. Investigations show that this network has the ability of learning, reminding, forgetting, concluding, pattern-recognition, classification of information and many other brain functions (Hertz et al. 1991). ANN is essentially made up of simple processing units called neurons (Foody et al. 1995). ANN structures are in the form of layers, which consists of an input layer, an output layer and one or more intermediate layers. Each layer contains several neurons that are connected by a network, which has different weights. Based on how the nodes are connected, the ANN is divided into two groups, feed forward ANN and feedback ANN. In the feed forward input applied to produce the output, neurons must be used as the pathway. A feed forward ANN is known as a "perceptron". Perceptron ANN is one of the most important and widely used aspects in diagnosis classification model (Picton 2000). Perceptron can be single-layered or multi-layered. The difference between single-layer and multi-layer perceptrons is the number of hidden layers between the input and the output layer. The task of these hidden layers is the extraction of the non-linear relationships of the input layer.

The two main steps that exist in the application of ANN are learning and recall. The aim of ANN learning is finding the optimal weights of neuron connections, which is achieved by the recursive method (Holland et al. 1989). Generally, the error back propagation learning rules are used to train the multi-layer perceptron ANN. The law of error propagation is composed of two main routes; the first route is called way-in path, where the input vector affects the multi-layer perception (MLP) network and impacts on the output layers through the intermediate layer. The output vector of the output layer is the actual response of the MLP network. In this way, the network parameters are fixed and unchanged. The second route is called the come-back path. In the come-back path, unlike the way-in path, the MLP network parameters can be changed and adjusted. This adjustment is consistent with the error correcting rule. The error signal at the output layer of the network is formed. The error vector is equal to the difference between the desired response and the actual response of the network. In the come-back path, the calculated error values are distributed in the entire network through the network layers. In this repetitive process, the corrected parameter weights are calculated and will be added to the previous weights and hence modified to prepare for implementation in the network (Wiszniewski 1983). In this algorithm, the network weights are based on the gradient method and the error signals are corrected and adjusted. Back propagation is used for explaining the correction of network behaviour, which is opposite to the weight communication between synapses (Wiszniewski 1983).

3 Genetic Algorithms

In 1960, Rechenberg presented the basic idea of evolutionary algorithms, where GA can be derived from. This is, in fact, a computerised search method, which is based on optimisation algorithms, named genes and chromosomes, developed at the Michigan University by Holland (Holland et al. 1989) and later by Freisleben & Merz (1996).

In this algorithm, due to being derived from nature, stochastic search processes are used for optimisation and learning problems (Sheta & Turabieh 2006). In nature, chromosome combinations will produce a better generation. Mutations occurring among the chromosomes may improve the next generation. GA solves these problems by using this concept (Sivanandam & Deepa 2010).

Overall operations of this algorithm are: fitting, selecting, combining and mutating (Ravagnani et al. 2005). In the algorithm process, an initial population of chromosomes is selected for the creation of a new and possibly better generation. Each chromosome has various arrays that should be optimised. After creating the initial population of merit (cost consumption) for each chromosome in the population the calculation is based on the objective function. The major parts of the costly (expensive) chromosomes are left behind and the cheaper chromosomes are kept to produce the next generation, the children. Among them, there are a number of elite chromosomes, which are considered to be cheap, and therefore remain untouched until the next generation. To determine the number of chromosomes needed for the evolution, parents are selected to produce offspring. Two chromosomes are selected as parents when they are combined. Sometimes genes are changed randomly. A mutation occurs and enables the algorithm to search for a wider area. In other words, a new generation can be created by reproductive processes of combining gene and mutation. This process must be repeated many times to achieve convergence and create an optimal solution (Haupt & Haupt 2004).

4 Height Interpolation Methods

The main purpose of using the known point height interpolation is the determination of the heights of the unknown's middle points. In 2004, Yang examined different methods for the interpolation according to the accuracy and applicability by using Surfer 8.0 software (Yang et al. 2004). These methods can be divided according to different criteria (Abdul-Rahman & Pilouk 2008). For example, interpolation methods based on surface coverage divided into local and global criteria. In the global methods, the height of all control points are used to estimate the heights for the unknown points, but in the local methods, calculation of unknown point heights are derived from the height of the neighbours' points. In this research, the different methods of interpolation are used to estimate the heights at the unknown points within the local methods, which are explained in the following sections.

4.1 *Inverse Distance Weighting Method*

In the inverse distance weighting (IDW) method, the height information of neighbouring points is used as a weight according to the distance to unknown points. Weight is a function of the distance from the unknown point and hence closer points have higher weights. For height calculation, the following equation is used

$$z = \frac{\sum_{i=1}^{n} \frac{zi}{d_i^p}}{\sum_{i=1}^{n} \frac{1}{d_i^p}}. \tag{1}$$

In (1), p is the speed reducer weight control rate according to distance, where it is equal to 2, d_i is the distance from unknown point to a well-known point and z_i represents the height of point i (Lu & Wong 2008, de Mesnard 2013).

4.2 *Polynomial Method*

This method approximates the surface using polynomial terms plain elements x, y in the form of $z = f(x, y)$. The n power of this polynomial equation is

$$z = \sum_{i=0}^{n} \sum_{j=0}^{n} a_{ij} x^i y^j \ . \tag{2}$$

Where x, y are turned parts and plain components of known points and a_{ij} are polynomial coefficients, which are determined using the know elevation values in the sample points and are obtained by least-squares portion.

4.3 *Kriging Method*

The Kriging method was introduced by Matheron (1963), based on the Krige variables theory zone (Krige 1951). This method is estimated based on a weighted moving average due to which the Kriging method of interpolation considers two criterions, the distance and the change of point elevation. It is the best unbiased linear varygram of weights with the minimal estimation of variance. This means that the difference between actual and estimated values is minimal. In the Kriging method, there are numerous techniques for computing the height values, which normally is divided into two different ways, ordinary Kriging and general Kriging. The ordinary Kriging is calculated based on (3):

$$z(x, y) = \sum_{i=1}^{n} \lambda_i z(x_i, y_i) \ . \tag{3}$$

Where z (x, y) is the height estimated at an unknown point, z (x_i, y_i) is the height of a sample point i and λ_i is the weight of point i.

For the estimation of the weight, various varygrams are used such as linear, exponential, Gaussian and spherical. The general Kriging method is also the combination of ordinary Kriging with local process. The local process can be defined in two ways, i.e. linear trend and quadratic.

4.4 *Nearest Neighbour Method*

In the nearest neighbour method, the nearest point to the unknown neighbour is selected and its height assumed based on the height of the unknown point. This method is an appropriate way if the data is taken based on a regular network and matching with the grid lines.

4.5 *Natural Neighbour Method*

The natural neighbour method was developed in 1980 by Sibson (1980). This method is based on a Voronoi Pattern for a set of separated points. A Voronoi Pattern is a diagram, which is dividing space into a number of regions. This method has more advantage compared with the nearest neighbour's method such as its ability to create a surface that is relatively smooth. This method is based on (4) (Sibson 1981):

$$z(x, y) = \sum_{i=1}^{n} \lambda_i z(x_i, y_i) \ . \tag{4}$$

Where z (x, y) is the estimated height at an unknown point, z (x_i, y_i) is height of sample point i and λ_i is the weight of a sample i followed by the area enclosed by any parts of the unknown sample point.

4.6 *Triangulation Method*

This method deals with the linear interpolation elevations based on a Delaunay triangulation (Zhong et al. 2008).

After the surface reconstruction with Delaunay triangles, the unknown height can be determined.

5 Data Assessment and Evaluation Criteria

In order to compare smart and ordinary interpolation methods, two areas are selected. Area 1 has been mapped by the existing software AutoCAD Civil 2D Land Desktop 2009 and area 2 presents new mapping data, 1:2000 in Port Khamir, which is located in Hormozgan State in the southern part of Iran. In both areas, a number of points are used as the control points. Other points are considered as the check points that are grouped in two series of check points and they are called check points type 1 and type 2. The characterizations and number of control points and two series of check points in both areas are shown in the Tabs. 1 and 2. Using control points and interpolation methods, the heights of the two series of check points (1 & 2) are obtained and it is compared with the actual height. Finally, the extent of errors that exist in the calculated elevations through interpolation methods can be determined by using the RMSE rate. The measurement of the RMSE can be expressed as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(z_{comp} - z_{actual})^2}{n-1}}. \quad (5)$$

Where, z_{comp} is the calculated height values and z_{actual} is the actual check point height.

6 Using Neural Networks in Heights Interpolation

The interpolation of elevations based on ANN uses the perceptron network, which consists of three layers, an input layer, an intermediate layer and an output layer. Structure and network topology is shown in Fig. 1. Two neurons in the input layer are components of x and y and the output layer of neuron is component of z. Training is based on the gradient method. In the network learning processes in both areas, control points are used for training and a set of check points. The check points type 1 are areas of validation and check points type 2 are the independent check points. These are used for testing and evaluating the precision interpolation networks. The error signal based on the RMSE is created and the correction of weight is used to achieve the minimum RMSE.

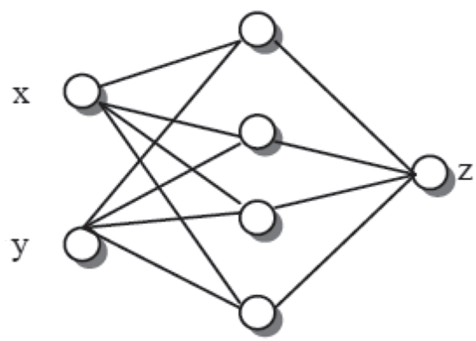

Fig. 1: Network perceptron with a hidden layer for the interpolation heights.

Tab. 1: Area Profile 1.

Elevation changes	No. of control points	No. of check points		Regional dimensions
		Type 1	Type 2	
16 m	100	45	40	250 × 275 m^2

Tab. 2: Area Profile 2.

Elevation changes	No. of control points	No. of check points		Regional dimensions
		Type 1	Type 2	
6 m	50	28	28	450 × 300 m^2

7 Using Genetic Algorithms in Heights Interpolation

Unlike ANN that is able to create a network for elevation interpolation, GA can only be used for the optimisation of usual methods of interpolation. The usual methods of interpolation used in this study along with GA have been optimised and are consisting of polynomials and the inverse distance weighting method, which will be described below.

7.1 *Using Genetic Algorithms in Polynomial Optimisation*

Heights of polynomials can be useful for the interpolation. The most common function to achieve this integration is the general polynomial function shown in Tab. 3 (Petrie & Kennie 1990).

It is clear that the single polynomial of a polynomial function has a special characteristic shape. Using specific terms, unique surface features can be created.

For the actual surface production in a particular model, it is not necessary to use the entire function. The operating system has the responsibility to determine what is used. Only in a few cases it is possible for the user to steer the function for modelling of the particular piece of land that is more relevant.

The first step of using of the polynomial functions is the determination of the optimal terms of these functions. The shape optimisation of the polynomials is related to the geometry and the topography of the region. GA is used to evaluate the effect of the presence or absence of various terms where the polynomial functions are used to find the most effective functions. For this purpose, a singular binary chromosome in the form of a series of zeros and ones is used. The digit zero indicates non-interference and the digit one indicates interference. In the process of GA, optimal chromosomes that show the best polynomial terms are obtained. Coefficients of the terms are determined by the least-squares method during this process. In this study, quartic polynomials are examined. For the GA optimisation, firstly the chromosomes must be formed and an initial population created. Each chromosome is made up of variables that are essentially the polynomial coefficients, which is interpreted as gene. Gene 1 represents in the desired term of polynomial and gene 0 represents the interference term in the polynomial. The first algorithm optimisation process consists of an initial population of chromosomes and the coefficients that can be calculated by control points through the least-squares method and using check points to determine the remaining residual. So by employing control points, check points and the dependent variable (RMSE), optimal chromosomes are formed. After finishing the optimisation processes, the check points, which had no interference in the optimisation process, are used to evaluate the obtained chromosomes. In other words, the process of determining proper polynomial coefficients with genetic algorithm and control points uses two types of check points. One is for the optimisation of the process under consideration of the control points to find the optimal chromosomes. They are referred to as GA check points (GACPs). The other are the independent check points used to evaluate the final chromosome, known as independent check points (ICPs). In this paper the check points type 1 and type 2 are referred to as GACPs and ICPs respectively.

Tab. 3: Polynomial function for surface reconstruction.

No. of variables	Description	Row	Equations
1	flat	zero	$z = a_0$
2	linear	first	"*flat*" $+ a_1x + a_2y$
3	quadratic	second	"*linear*" $+ a_3x^2 + a_4y^2 + a_5xy$
4	cubic	third	"*quadratic*" $+ a_6x^3 + a_7y^3 + a_8x^2y + a_9xy^2$
5	quartic	fourth	"*cubic*" $+ a_{10}x^4 + a_{11}y^4 + a_{12}x^3y + a_{13}x^2y^2 + a_{14}xy^3$

7.2 *Using Genetic Algorithms in the Optimisation of Inverse Distance Weighting Method*

GA, control and check points can be used to optimise the magnitude of strength and consequently a proper weight is achieved. In this article, from the control points and the series of check point type 1 the GACPs can be used to determine the optimised strength. Finally, the strength obtained from GA is substituted in the IDW equation and as a result, the accuracy of the algorithm with the series of check point type 2 as the independent check points through the optimisation process with GA (ICPs) are examined and evaluated. The tournament function can be used for the selection and the Gaussian function for the mutation (Eremeev 2000). The fusion function is a single-point combination for generations while 500 generations are considered in a GA process.

8 Assessment of Results

The IDW interpolation method was applied to the datasets using three different settings of the power values of the inverse distance method (Tab. 4).

Tab. 4 shows the RMSE for both datasets in the unit metre. The minimal errors can be observed with a power value of one and three in the first dataset, and three in the second dataset. Area 2 is comparably flat which explains that the best fit is found at the highest power

Tab. 4: Results obtained from IDW method.

Inverse distance power	RMSE for area 1 (m)		RMSE for area 2 (m)	
	Check points type 1	Check points type 2	Check points type 1	Check points type 2
1	1.601	1.895	0.849	1.115
2	2.130	2.375	0.744	1.005
2	1.661	1.865	0.684	0.931

Tab. 5: Results of the Kriging method.

Type of varygram	Type of Drift	RMSE for area 1 (m)		RMSE for area 2 (m)	
		Check points type 1	Check points type 2	Check points type 1	Check points type 2
Spherical	No drift	4.409	4.656	0.938	1.201
	Linear drift	2.061	2.392	0.638	0.850
	Quadratic drift	1.264	1.391	0.888	1.148
Exponential	No drift	4.409	4.656	0.939	1.203
	Linear drift	2.061	2.392	0.638	0.849
	Quadratic drift	2.060	2.391	0.890	1.151
Linear	No drift	1.219	1.374	0.648	0.900
	Linear drift	1.261	1.383	0.652	0.886
	Quadratic drift	1.260	1.383	0.647	0.898
Gaussian	No drift	4.409	4.656	0.939	1.203
	Linear drift	2.061	2.392	0.638	0.849
	Quadratic drift	2.060	2.391	0.890	1.151

value. On the other hand area 1 has a strongly undulated terrain. High power values cause a smoothing effect to the data and are therefore not appropriate to model this type of terrain. Thus, the lower power value fosters the best fit. This shows that the selection of an optimal power value is very important for a better interpolation and GA can be useful for height interpolation by the IDW method in rough surfaces. In comparison, Kriging uses several interpolation methods for the varygrams such as spherical, linear, exponential, and Gaussian. In each case, the drift types "no drift", "linear drift" and "quadratic drift" are used. The results are compared in Tab. 5.

Tab. 5 shows that the accuracy of the Gaussian and exponential varygrams are nearly the same while the highest accuracy is achieved using a linear varygram with no drift for area 1 and exponential or Gaussian linear drift for area 2.

In spherical, exponential and Gaussian varygrams, linear and quadratic drifts are more accurate compared to no drift, but in a linear varygram no drift is more accurate. Results of other methods are shown in Tab. 6.

One of the predominant properties of the Kriging method is smoothing. Therefore, the Kriging method has a lower accuracy in regions with high elevation changes that have

Tab. 6: Results obtained from other conventional interpolation methods.

Method	RMSE for area 1 (m)		RMSE for area 2 (m)	
	Check points type 1	Check points type 2	Check points type 1	Check points type 2
Natural neighbour	1.261	1.383	0.888	1.148
Nearest neighbour	1.224	1.400	0.633	0.874
Triangulation	1.224	1.400	0.633	0.874
Quartic polynomial	2.444	2.277	0.675	0.917

Tab. 7: Results from IDW optimisation method with GA (GACP = GA check point, ICP = independent check point).

	RMSE for area 1 (m)		RMSE for area 2 (m)	
Indices optimisation	2.531		2.07	
RMSE (m)	**GACP**	**ICP**	**GACP**	**ICP**
	0.762	0.920	0.648	0.881

Tab. 8: Results of quartic polynomial optimisation with GA.

Power of polynomials	No. of variables	RMSE for area 1 (m)		RMSE for area 2 (m)	
		GACP	ICP	GACP	ICP
4	15	0.662	1.115	0.466	0.684

Tab. 9: Results of interpolation using ANN.

No. of neurons in hidden Layer	RMSE for area 1 (m)	RMSE for area 2 (m)
	Check points type 2	Check points type 2
5	0.607	0.524
10	0.566	0.488

a rough surface and sharp edges. There are many factors that affect the accuracy of the Kriging method such as the number of samples and their distance in between. In the small domain of changes, the accuracy of the Kriging method and other methods are comparable. Area 2 has a small domain of elevation changes and the accuracy of the Kriging interpolation and other methods are nearly equivalent.

In contrast to Kriging, the GA in combination with control points and check points can be adapted to the terrain type by selecting an appropriate power value for the IDW method. An independent evaluation took place by using the check points type 2. Tabs. 7 and 8 compare the results that are achieved by using GA/IDW method with the quartic polynomial optimisation.

In ANN interpolation, the control points are used for training and a series of check points type 1 for validation and for testing/evaluating. Check points type 2 are used for the perceptron network with a hidden layer of 5 neurons and 10 neurons (Saati et al. 2008, Karabork et al. 2008), considering the first period size and with momentum 0.7 Ns, the following results have been obtained.

In order to compare and evaluate the interpolation methods, the results of the current methods and AI techniques are collected from the RMSE through a series of check points type 2. The reason for this is that the AI techniques at the series of check points type 1 for the optimisation process of interpolation parameters in GA and for the network validation in ANN can be used. Therefore, to ensure that the results of the optimisation process are valid, a series of check points type 2 is used as the independent check points. Consequently, the RMSE rates obtained from the conventional interpolation methods and AI techniques are compared with a series of check points type 2, which is represented in Fig. 2 as a line graph.

Fig. 2 shows with regards to area 1 (16 m altitude) that the quartic polynomial method produces the worst results. In the second region (area 2) that is wider compared to area 1 and only has 6 m altitude, the triangulation method produces better results. Thus, due to better triangles obtained in flat regions in regards to the other region, where there are greater changes in altitude, better results are achieved.

In both regions, the Kriging method for interpolation produces better results. The results

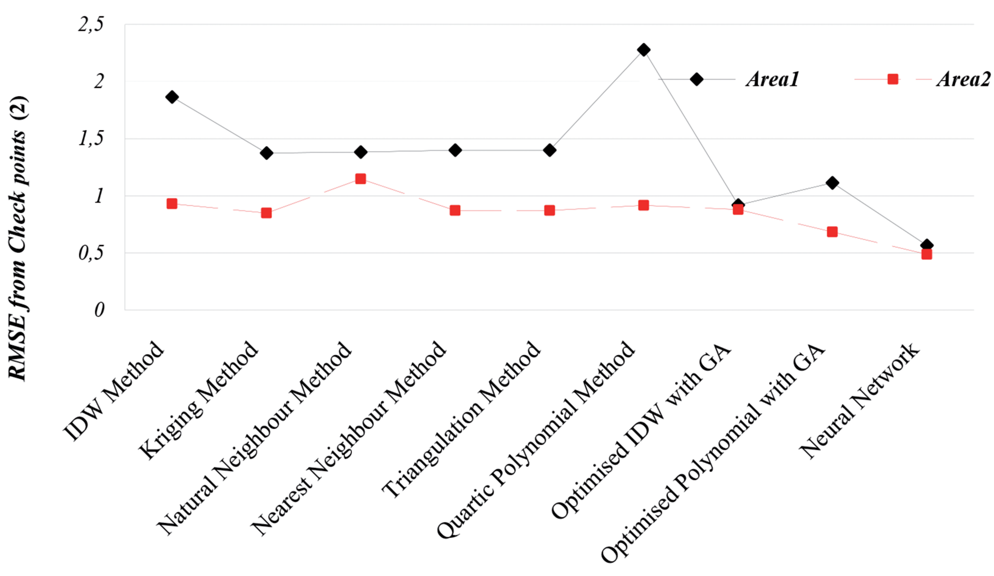

Fig. 2: Comparison of results of different interpolation methods.

of the Kriging method are very sensitive to the selection of the interpolation method of the varygram. Area 2 has a small domain of elevation changes and the accuracy of the Kriging interpolation and other methods are nearly equivalent. The Kriging method has the highest accuracy compared to other conventional methods.

In both regions, AI techniques results in a better accuracy rather than conventional methods. However, in the first region, AI techniques produce better accuracy, while the second region shows little accuracy difference with respect to conventional methods. Among the AI techniques within both regions, the best accuracy exists within ANN because it has a high ability for pattern recognition and function approximation. The quartic polynomial and the IDW that are optimised by GA have lower accuracy than ANN and better accuracy than other methods respectively for area 1 and area 2. These results show that the GA is very useful for IDW optimisation. In both areas, the IDW has a low accuracy in comparison to other conventional methods. However, with the estimation and the extraction of optimal power values and proper weight by GA, the accuracy of the optimised IDW is higher than conventional IDW. Also in area 1, the quartic polynomial has the lowest accuracy. However, by using GA and the extraction of optimal terms, the accuracy of interpolation and modelling is increasing significantly.

9 Summary and Conclusion

In the evaluation of the results, it is concluded that the use of AI techniques for height interpolation is effective and has a higher level of accuracy compared to conventional methods, especially in areas with high elevation. In order to achieve the best method for polynomial interpolation GA is used and optimal weighting parameters are achieved by the IDW method. ANN is able to determine an appropriate weight to indicate the best estimated elevation in unknown altitude regions.

Among the entire interpolation methods mentioned (conventional and intelligent), the aim is to evaluate the accuracy of interpolation methods. Universal interpolation occurs in the entire surrounding regions and as a result can be suggested for larger regions, which can be divided into smaller regions with respect to altitude changes. Within each of the smaller regions a universal interpolation can be applied. Consequently, the most important problem of distance for both conventional and intelligent interpolation methods can be solved. Also, by using universal interpolation, the time for the optimisation in GA and the training time in ANN can be reduced and thus the difficulty of applying intelligent methods in large regions with numerous sample points decreased.

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