MINISTRY OF EDUCATION AND TRAINING
HANOI UNIVERSITY OF MINING AND GEOLOGY

NGUYEN THI THU HUONG

RESEARCH ON ACCURACY IMPROVEMENT OF THE GRID DIGITAL ELEVATION MODEL USING HOPFIELD NEURON NETWORK

MAJOR: SURVEYING AND MAPPING ENGINEERING

CODE : 9520503

SUMMARY OF THE DOCTORAL THESIS

HA NOI – 2021

The thesis has been completed at the **Department of Surveying and Geomatic analysis, Faculty of Geomatics and Land Administration, Hanoi University of Mining and Geology**

Supervisor:

Assoc. Prof. Dr Nguyen Quang Minh,
Hanoi University of Mining and Geology

Reviewer 1: **Prof. Dr Vo Chi My,**
Vietnam Association of Georaphy, Cartography and Remote sensing

Reviewer 2: **Dr Nghiem Van Tuan,**
Department of National Remote Sensing

Reviewer 3: **Assoc. Prof. Dr Nguyen Tien Thanh,**
Hanoi University of Natural Resources and Environment

The thesis will be defended before the Examination Board at Hanoi University of Mining and Geology at…. o'clock dated ………

The thesis could be retrieved from:

National Library – Hanoi,
Library of Hanoi University of Mining and Geology

INTRODUCTION

1. The necessity of the thesis

The high resolution and accuracy of the Digital Elevation Model (DEM) will be more detailed the topographic surface can be shown, from which the analysis results from DEM will give higher accuracy. However, the building a high accurate DEM requires high costs and a lot of difficulties. In contrast, for low-precision DEMs (DEMs from satellite data such as ASTER or STRM) with medium resolution (30m - 90m), a very high coverage area has been built up and they are provided free of charge (https://earthexplorer.usgs.gov). But the application of these DEMs is quite limited due to the lack of precision required. Therefore, if it is possible to increase the accuracy of existing DEMs instead of building the new DEMs with higher precision (with higher resolution), it is essential and meaningful.

From the above-mentioned arguments, the topic of the thesis: *"Study on the accuracy improvement of the grid Digital Elevaion Model using Hopfield neuron network"* was raised.

2. Purpose, objects and scope of the study

The purpose of the dissertation is to test and use different accuracy assessment methods to evaluate the improvement of grid DEMs accuracy when increasing resolution by popular resampling methods. Currently and building the algorithm and programs to increase the spatial resolution and accuracy of the grid DEM using Hopfield neural networks. Objects of the study are grid DEMs which are built from different methods such as: LiDar DEM, contour and field measurements. The scope of the study includes the spatial resolution and accuracy of the above grid DEMs.

3. Tasks of the study

Study on the building algorithms and programs to increase spatial resolution and accuracy of grid DEMs using Hopfield neural network; qualitative and quantitative assessment of the popular resampling methods to increase the resolution of grid DEMs.

4. Methodology

The methods used in the study include statistical analysis methods, experimental methods, comparison methods, methods of modeling and expert methods.

5. Scientific and practical significance

The thesis analyzed, proposed and confirmed the correctness of the algorithm to improve the accuracy of the DEM grid by using the Hopfield neural network. Establishing the science in each research direction, proposed in the thesis, opens a new approach to improving the accuracy of grid DEMs.

By testing the actual data to confirm each study, the research results in this thesis can be completely applied in practice, contributing to reducing the effort and cost in building DEM grids with resolution. solving and high accuracy; offer products with the best application for different fields of life, especially in topographical analysis, geomorphology, and natural resource management.

6. Hypothesis

Hypothesis 1: The popular resampling methods (Bilinear method, Bi-cubic, Kriging) improve accuracy of the Digital Elevation Model in grid form;

Hypothesis 2: The algorithm to improve the accuracy of Digital Elevation Model (DEM) in grid form using Hopfield neural networks is allowed to increase the spatial resolution and accuracy of the grid DEMs.

7. New points of thesis

1. It has been tested to confirm that the popular resampling methods such as Bilinear, Bi-cubic and Kriging are improved the accuracy of the Digital Elevation Model and assesement accuracy of the popular resampling methods according to a new approach.

2. This is the first time, it has successfully studied and applied the artificial neural network theory in increasing resolution and improving the accuracy of the Digital Elevation Model (DEM) in grid form.

3. It has been developed a program to increase spatial resolution and accuracy of a grid Digital Elevation Model using Hopfield neural networks.

8. Structure of thesis

The thesis consists of three chapters with introduction and conclusion, and references. Here is the structure of the thesis:

Introduction

Chapter 1. Literature review on Digital Elevation Model, neuron networks, Hopfiled neuron network and the application of Hopfiled neuron network in optimization algorithms.

Chapter 2. Research on the improvement accuracy of grid DEM using popular resampling methods.

Chapter 3. Research on the improvement accuracy of grid DEM using Hopfield neuron network method.

Conclusions and recommendations.

List of publications related to Ph.D. thesis.

References.

Appendix.

CHAPTER 1
LITERATURE REVIEW ON DIGITAL ELEVATION MODEL, NEURON NETWORKS, HOPFIELD NEURON NETWORK AND THE APPLICATION OF HOPFIELD NEURON NETWORK IN OPTIMIZATION ALGORITHMS

1.1. Literature review on Digital Elevation Model

1.1.1. The concept

Digital Elevation Model (DEM) represents the terrain surface in 3D in digital formats. The 3D terrain surface is modeled with a function of the form z = f (x, y) where each point (x, y) in the D plane is attached to an elevation value f (x, y) (De Floriani & Magillo, 2018).

1.1.2. The structures of the Digital Elevation Model

The basic structure of DEM comes from the data models which are used to represent it. There are many different methods to create DEM surface: grid DEM model, TIN model or math model (Cuong, 2006). In the above methods, the grid DEM model is used a lot because it has a simple and easy form to analyze surface information (Vieux, 1993).

1.1.3. The methods of establishing digital altitude model (DEM)

According to Florinsky (Florinsky Igor, 2012) and Nelson (Nelson, 2009), DEM can be generated from many different sources such as: from field measurement results, from digitized data on maps, from aerial and satellite imagery measurements, from Radar measurements data, from UAV measurement data, etc.

1.1.4. The accuracy of DEM

The accuracy of DEM is determined by the similarity between the defined height on the DEM surface of a point and the actual height value. There are two quantities that can characterize the elevation accuracy of the DEM surface, which has been used extensively in previous studies: the Root Mean Square Error (RMSE) and the Mean Error (ME) (Mukherjee et al., 2013).

1.1.5. The applications of DEM

DEM has many applications in fields such as natural resource management, transportation, communication, navigation, construction, civil, military, ... In which, DEM has a great role in results analysis, decision making and product development.

1.1.6. Several studies have demonstrated the improvement and accuracy of DEM

Some of the typical studies on DEM accuracy improvement and evaluation are presented in the documents: [1], [3], [5], [9], [10], [11], [12], [13], [72], [74].

1.2. Literature review on neuron networks

1.2.1. Concept and structure of artificial neural networks

Neural networks are a new computational method based on biology to simulate some functions of the human brain. The two main components that make up a neural network are artificial neurons (simulating nerve cells) and synapses (simulating nerve junctions). Neurons are the basic information processing units of neural networks. Each neuron is a computational unit that has many inputs and one output, each input coming from a synapse.

1.2.4. Classification of neural networks

There are many different types of networks and there are also many ways to classify neural networks (Kohonen, 2012). Based on the number of layers in a neural network, we can classify it into: single-layer neural networks, multi-layered neural networks. Based on signal pathways in neural networks, we classify them into: linear neural networks, feedback neural networks, self-organizing neural networks.

1.2.5. Characteristics of artificial neural networks

Neural networks do not have access to the intricacies of the brain. But there are two basic correlations between neural networks and biological neurons. Links between neurons determine the function of the network.

1.2.6. Application of Neural Network

Some common applications of neural networks today: in the field of space, manufacturing automatic controllers for engines, banking, defense, electronics, medicine, entertainment, main ... and in the field of Geodesy - Map (in forecasting tasks, optimization problems, etc.).

1.2.7. Hopfiled neural network

In 1982, Hopfield gathered some earlier research and presented a complete mathematical analysis based on Ising spin models to give birth to the

Hopfield network (Hopfield, 1984). Hopfield neural networks are fully regression connected networks and they are mostly used for automatic binding and optimization.

1.3. The applications of Hopfield neural network in optimization problems

Hopfiled neural networks have been successfully applied in many fields: solving combinatorial optimization problems [83] ..., optimizing spatial dependencies [50, 73].

1.4. General assessment of the research situation and research direction of the thesis

Increasing the spatial resolution and improving the accuracy of the existing low resolution grid DEM is essential, scientific and practical.

There have been studies and experiments on how to increase the resolution of grid DEM by the popular redistribution methods: Bilinear, Bi-cubic, Kriging, but there are no studies that confirm that That variable can also improve grid DEM accuracy. Furthermore, the methods of such redistribution have not been comprehensively evaluated for accuracy.

On the basis of the above meaning and shortcomings, this thesis aims to confirm that those common redistribution methods can also improve the accuracy of grid DEM and propose a completely new method to increase grid DEM's efficient and highly reliable spatial resolution and accuracy.

1.5. Conclusion chapter 1

In this chapter, the thesis introduces an overview of DEM and neural networks. The thesis also introduced some typical studies on the improvement, assesement the accuracy of DEM and applications of Hopfiled neural network in optimization problems.

On the basis of researched issues that have not been fully resolved, in this thesis, new research contents are proposed.

CHAPTER 2
RESEARCH ON ACCURACY IMPROVEMENT OF GRID DEM USING POPULAR RESAMPLING METHODS

2.1. Grid DEM accuracy assessment methods

The accuracy of the DEM grid data is done by both visual assessment methods and quantitative assessment methods.

2.2.1. Visual assessment methods

2.2.1.1. Using the direct comparison method

In this method, two images of two DEM datasets are directly compared with the eyes to see the similarities or differences..

2.2.1.2. Using the cross-section method

Compare two DEM surfaces based on cross sections: based on the elevation point values of DEM datasets, calculate and plot the respective longitudinal and cross sections of the resulting DEM data after resampled and the sample DEM data at the same resolution. The comparison between those respective sections is then carried out. If the cross-sections of the resulting DEM of the redistribution methods are closer or closer to that of the sample DEM, the closer that DEM surface is to the sample DEM surface (reference DEM), that is, the DEM data have higher accuracy (less deviation compared to sample DEM).

2.2.1.3. Comparison by scatter charts method

From the elevation point data of the DEM tuples, construct scatter plots of these datasets. Then compare the two DEM surfaces using a scatter plot. In these scatter plots, the closer the points on the scatter plot are to the regression line, the closer the two DEM surfaces will be, and if the points are far from the regression line, the two DEM surfaces do not match.

2.2.2 Quantitative assessment methods

2.2.2.1. Using the Root Mean Square Error value

The Root Mean Square Error value (RMSE) represents the deviation between the elevation data in the reference DEM and the resulting DEM of the resampling methods, which is represented mathematically as follows:

$$RMSE_Z = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(Z_{di} - Z_{ri})^2} \qquad (2.1)$$

In which: $RMSE_Z$ is the Root Mean Square Error value; Z_{di} is the height value of point i on the DEM surface resulting from the resampling method; Z_{ri} is the height value of point i on the reference DEM surface; n is the number of test elevation points.

2.2.2.2. Using R statistic value (Correlation coefficient) and regression equation represented by 2 parameters m and b

In the thesis, to assess the accuracy of the results in different methods, linear regression models were attached to the relationship between the reference data and the resampled data. The similarity of the two types of DEM can also be quantitatively assessement using linear regression coefficients (*m*, *b*) and the correlation coefficient *R*.

2.2. Some popular redistribution algorithms to increase spatial resolution for grid DEM

2.1.1. Bilinear resampling method

In mathematics, bilinear interpolation is an extension of linear interpolation to interpolate functions with two variables (e.g. x and y) on a 2D plane grid. Bilateral interpolation is performed using linear interpolation in one direction first, then in the other.

2.1.2. The interpolation algorithm based on Nearest Neighbor method

The Nearest Neighbor interpolation algorithm will choose the interpolation point value as the value of the nearest point, completely not considering the value of other neighbors to calculate the interpolation.

2.1.3. Bi-cubic resampling method

While the Bilinear interpolation method only considers 4 pixels (2x2), the calculation of Bi-cubic interpolation takes up to 16 pixels (4x4). The Bi-cubic interpolation method is usually computationally complicated, so it takes more time to generate the output than two bilinear interpolation methods or the Nearest Neighbor based interpolation method.

2.1.4. Kriging interpolation method

Kriging is a geographic interpolation technique that considers both the distance and the degree of variation between known data points to estimate the value of points in undefined areas. The essence of the Kriging interpolation method is to predict the value of the function at a certain point by calculating the weighted average of known points in the vicinity of the interpolation point.

2.3. Experiment to increase the spatial resolution of the grid DEM by popular resampling methods

2.3.1. Experimental data

The thesis uses four DEM datasets for experiment. The spatial resolution for all four experimental DEM datasets in this study was chosen to range from 5m to 90m and for which a zoom factor value was 3 or 4. Two data types were used for the assessment accuracy of DEMs which are increased resolution by popular resampling methods are: Degraded DEMs and real DEM datasets (Sampled DEM).

The first reduced resolution DEM dataset (D1) is in the Yen Thanh - Nghe An area, 3.5 km x 3.5 km, produced from topographic maps at scale 1: 10,000. The resolution of the original DEM was initially 20m. This DEM is reduced in resolution to 60m, used as input data to the algorithms. The second reduced resolution DEM dataset (D2) is the 30m DEM SRTM, provided by USGS Earth Explorer. This data set also covers in the same area as D1 dataset. This data is reduced to 90m resolution as input data for the algorithms. The first real DEM dataset (S1) for Mai Pha-Lang Son area, collected by direct measurement in the field, has an area of 200m x 200m. The second real DEM dataset (S2) consisted of 533 elevation points, collected by direct field measurements, and then interpolated Kriging to produce a DEM 5m resolution, used as reference DEM data.

2.3.2. Experimental results and assessment accuracy

2.3.2.1. Visual assessment by direct visual comparison

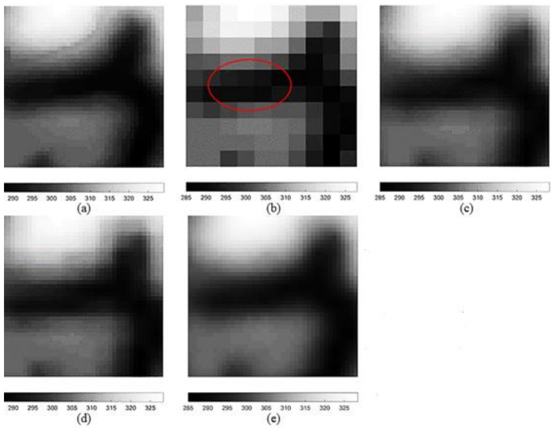


Figure 2.1. Lang Son DEM data after increasing resolution

In which: (a)-referenced DEM data in 5m resolution; (b)- reduced DEM data in 20m resolution (as input to the algorithms); (c)-DEM 5m resolution is interpolated bilinear method; (d)-DEM 5m resolution is interpolated Bi-cubic method; (e)-DEM 5m resolution is interpolated Kriging method.

2.3.2.2. Visual assessment using cross section

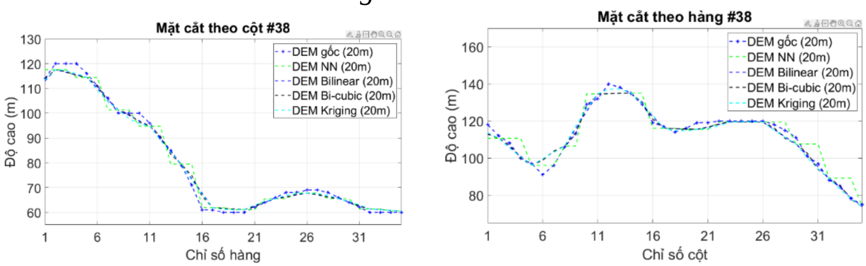
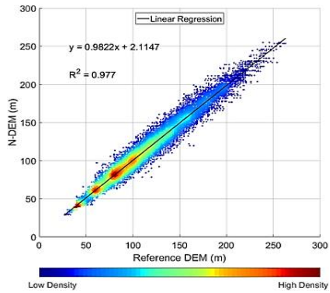
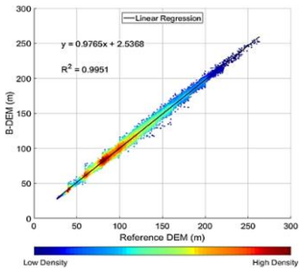


Figure 2.2. Some example cross sections (a column section and a row section of D1 dataset - reduced DEM data 20m in Nghe An area)

2.3.2.3. Visual assessment by scatter chart

(a)





(b)

Figure 2.3. Some example scatter charts for 20m resolution reduced DEM dataset in Nghe An area

In which: (a)-Scatter chart of input DEM and reference DEM; (b)-Scatter chart of DEM is interpolated Bilinear method and referenced DEM.

2.3.2.4. Quantitative evaluation using the Root Mean Square Error value

The results of the above quantitative evaluation show that: the method of increasing the spatial resolution of the grid DEM model according to the re-dividing methods gives higher accuracy than the original DEM when running the test on all four sets. DEM data.

2.3.2.5. Quantitative assesement using R statistic value (Correlation coefficient) and regression equation (represented by two parameters m and b)

The *m* and *b* values reflect the influence of the systematic error in DEM while the R^2 values reflect the random error part. The experimental results all show that: for all three methods of resampling, there is a decrease in the composition of random error and systematic error compared with the original DEM without increasing resolution.

2.3. Conclusion chapter 2

When assessment accuracy of grid DEMs which are increased resolution by resampling methods according to the new more comprehensive approach of the proposed's author, all 4 datasets showed a increase in accuracy with resampled DEMs, especially from the Kriging method, compared with the original DEM. However, the analysis also showed that resampled DEMs contain some systematic errors that cause the surface of DEM to be higher than it actually is at the depressions, convergence and tendency the lower the higher the points, the lower the hydrolysis line.

CHAPTER 3
RESEARCH ON THE IMPROVEMENT ACCURACY OF GRID DEMs USING HOPFIELD NEURON NETWORK

3.1. Scientific basis of Hopfield neural network (HNN) application algorithm to increase spatial resolution and accuracy of grid DEMs

The HNN model for grid DEM is a development from the Hopfield neural network model designed for Tatem's overlay map super-resolution algorithm (2001). Since the remote sensing images and the grid DEMs both have raster data structures, it is expected that the HNN methods developed for remote sensing images can be improved to increase the accuracy as well as the level of detail of the grid DEMs.

3.2. Hopfield neural network applied to increase spatial resolution and improve the accuracy of grid DEMs algorithm

3.2.1. Build the model, set up the target functions and condition functions for the algorithm

To use the Hopfield neural network model to increase the resolution of the grid DEM, we will divide one pixel in the original DEM in low resolution with large pixel size into $m \times m$ sub-pixels, each sub-pixel is represented by a neuron in the HNN and the elevation value is the output of the neurons in the Hopfield neural network. The output value is also the height value of each neuron (sub-pixel) that will be determined through the target function to ensure that the semi-variogram value between neighboring neurons approaches the minimum value. In addition, the elevation values of each sub-pixel are bounded by the conditional function that the mean elevation value of the sub-pixels within the range of one pixel in the original DEM must be equal to the pixel's elevation value on the original DEM.

Spatial dependence is defined here as the similarity in value between pairs of points that are closely spaced, meaning that the semi-variogram $\gamma(h)$ value will be small when the distance lag h between two points (i, j) and $(i, j + h)$ are small. For DEM model with increased resolution, if there is spatial dependence between sub pixels, the semi-variance coefficient will be small at small h increments. This means that when the semi-variogram coefficient is minimized, the spatial dependency maximization function in this new HNN model will increase or decrease the output value of the sub pixel located at the center until when equal to the mean height of the surrounding sub pixels.

To find the minimum value of the function *γ (h)* (3.1), it is necessary to use the derivative value of this function (3.2).

$$\gamma(h) = \frac{1}{2N(h)}\sum_{1}^{N(h)}\left[v_{ij} - v_{ij+h}\right]^2 \quad (3.1)$$

In which: *γ (h)* is the value of the semi-variogram coefficient in the distance lag *h*, *h* is the distance between a pair of sub pixels with height values: v_{ij} , v_{ij+h} and *N (h)* is the number of pairs of points separated by a distance *h*.

$$\frac{\partial\gamma(h)}{\partial v} = 0 \quad (3.2)$$

And $\frac{\partial\gamma(h)}{\partial v} = \frac{\partial\left(\frac{1}{2N(h)}\sum_{1}^{N(h)}(2v_{ij}-2v_{ij+h})\right)}{\partial v} = v_{ij} - \frac{\sum_{1}^{N(h)} v_{ij+h}}{N(h)} = 0$

From that: $$v_{ij}^{expected} = \frac{\sum_{1}^{N(h)} v_{ij+h}}{N(h)} \quad (3.3)$$

The elevation values are changed as follows:

$$du_{ij}^{sd} = v_{ij}^{expected} - v_{ij} \quad (3.4)$$

This means that the elevation value of the middle sub-pixel with elevation value v_{ij} will be equal to the mean elevation value of the surrounding sub-pixels with *h* (v_{ij+h}) distance lag.

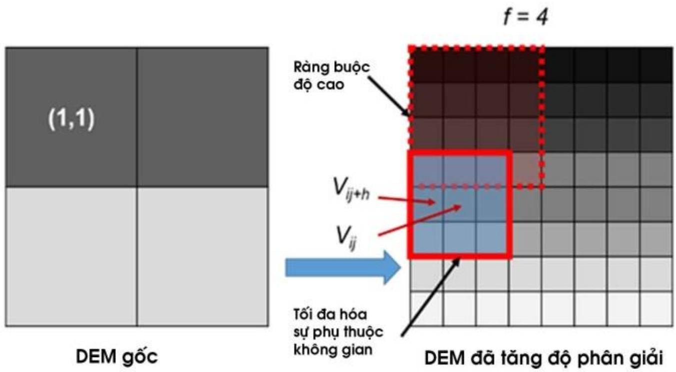


Figure 3.1. HNN model is used to increase the resolution of grid DEM

In Figure 3.1 shows an example of the proposed new model to increase the pixel size of *(2 x 2)* pixel grid DEM. One pixel in the original DEM is divided into (*4 × 4*) sub pixels in the new DEM (zoom factor *m = 4*). So, from an original (*2 x 2)* DEM is resampled into a DEM of (*8 × 8*) sub pixels. Each sub pixel is represented by a neuron in the HNN model and has the initial value of the pixel's elevation value in the original DEM (or may be randomly assigned). The simulated elevation of the sub-pixel after maximizing the spatial dependence is calculated using a (3×3) window and the middle sub-pixel elevation value is equal to the average of elevation values of 8 sub-pixels around.

If the function to maximize spatially dependent space is the only function used in the model then the elevation values of all sub-pixels in the new DEM (after increasing resolution) will eventually be the same. Therefore, the elevation value of the original DEM will not be retained. To solve this problem, it is necessary to use a conditional function for binding. The principle of this function is that the average values of all sub-pixels in a pixel must be equal to the elevation value of that pixel in the original DEM. For example, the average of elevation value of all sub-pixels in a pixel (*1,1*) of the original DEM in Figure 3.1 should be equal to the elevation value of pixel *(1,1*).

The input value of each neuron (sub pixel) is calculated based on formula (3.5) with the value du_{ij} / dt of:

$$\frac{du_{ij}}{dt} = \frac{dE_{ij}}{dv} = du_{ij}^{sd} + du_{ij}^{ep} \qquad (3.5)$$

From here we can calculate the energy function E of the entire Hopfield neural network at time *t* is:

$$E = \sum_i \sum_j \left(du_{ij}^{sd} + du_{ij}^{ep} \right) \qquad (3.6)$$

The HNN model will run until the energy function E reaches minimum value.

3.2.2. The block diagram of the algorithm

The figure 3.2 is a block diagram of increasing spatial resolution of DEM using Hopfield neural network algorithm (example illustration of increasing the spatial resolution of DEM from 20m to 5m).

3.2.3. Design a program to increase spatial resolution and improve grid DEM accuracy using a Hopfiled neural network

The figure 3.3 is the program of increasing spatial resolution and improvement accuracy of a grid DEM using Hopfield neural networks which is programmed in Python language and integrated on the QGIS software.

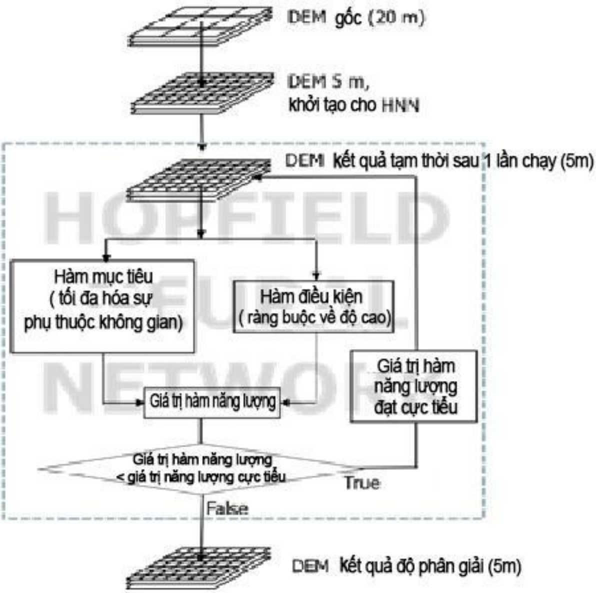


Figure 3.2. The block diagram of increasing spatial resolution of DEM using Hopfield neural network algorithm (example illustration of increasing the spatial resolution of DEM from 20m to 5m

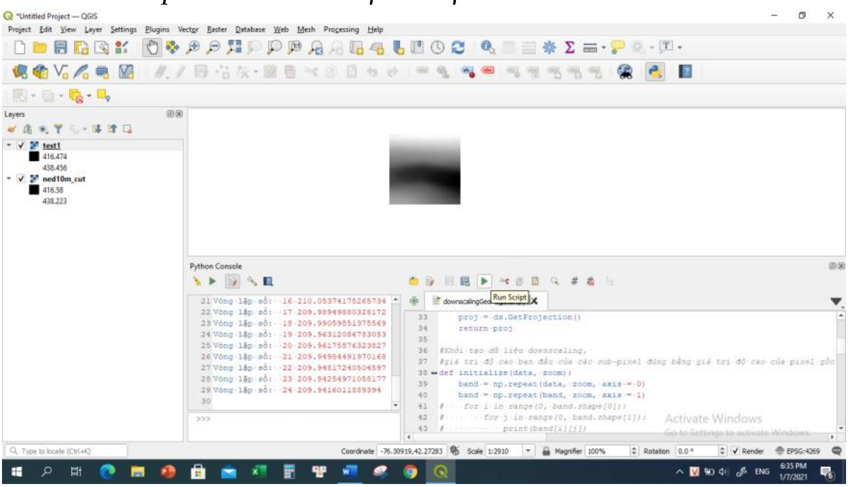


Figure 3.3. The program of the increasing spatial resolution and improvement accuracy of a grid DEM using Hopfield neural networks

3.3. Experiment to increase the spatial resolution and accuracy of the grid-type digital model by using Hopfield neural networks (modified HNN model)

3.3.1. Experimental data

In order to easily compare the performance of the algorithm with the widely used re-dividing methods such as Bilinear bilinear, Bi-cubic, and Kriging bilinear, this chapter 3 uses the same input data sets that have been used. These algorithms are used to evaluate these algorithms in Chapter 2. In those 4 experimental data sets, there are 2 DEM datasets built on the principle of reducing resolution and 2 DEM datasets built from real data. practice. Two data sets were constructed using the principle of reducing resolution from standard data, Data sets D1 and D2 in Yen Thanh, Nghe An area. Standard DEM data of D1 dataset has a resolution of 20m, which is then reduced resolution to 60m for use as input to resolution increasing models by bilinear, Bi-cubic, Kriging algorithms and HNN.

In addition to the 4 datasets described above, a group of field direct measurements were used to evaluate the model. This data includes 236 altitude points determined by the electronic total station in the same area of the data set to establish the Lang Son DEM 20m and 5m with equivalent accuracy.

3.3.2. Experimental results and assessment of accuracy

3.3.2.1. Visual assesement by direct visual comparison

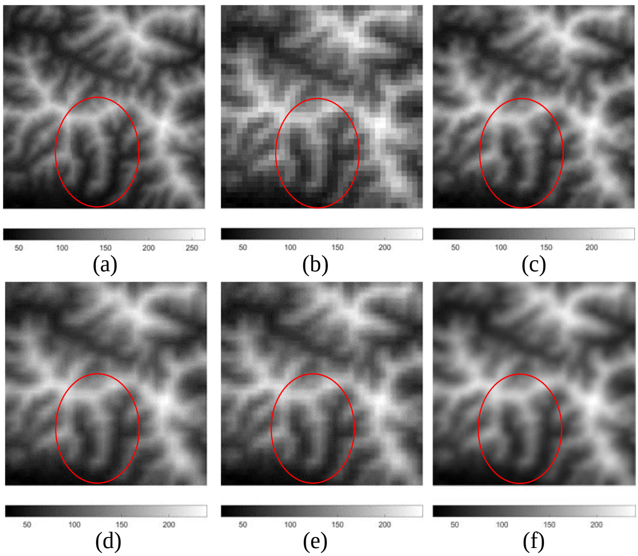


Figure 3.4. Example of increasing spatial resolution of DEM in Yen Thanh, Nghe An area from 60m to 20m resolution (dataset D1)

In which: (a)-DEM data referenced at the resolution of 20m; (b)-DEM data reduced to 60m resolution, as input to the algorithms; (c)-DEM after increasing resolution from 60m to 20m by using HNN method; (d)-DEM after increasing resolution to 5m bilinear method; (e)-DEM after increasing resolution to 5m Bi-cubic method; (f)-DEM after increasing resolution to 5m Kriging method.

Visual comparison shows that the DEMs although the bilinear and Kriging methods improved the image of the DEM to be quite similar to the reference DEM, improving the breakage level due to low resolution, but the result after increasing resolution by the proposed new HNN model still improves DEM images much better than the resampling methods. This is true for all four experimental datasets.

3.3.2.2. Visual assessment using cross section method

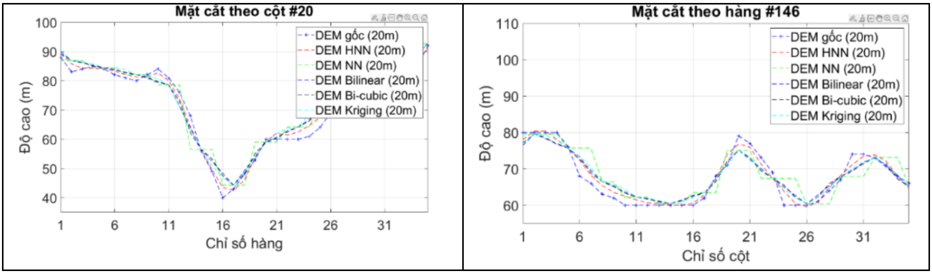


Figure 3.5. Some example cross sections (a column section and a row section of D1 dataset - reduced DEM data 20m in Nghe An area)

The experimental results all show that: the method of increasing resolution by HNN model is much more accurate than the popular resampling methods (Bilinear, Bi-cubic, Kriging) with typical terrains, especially, where there is great change in elevation such as the peaks of mountain, ranges and hills or valley bottom, especially V-shaped valleys, edges and hills with sharp peaks.

3.3.2.3. Visual assessment by scatter chart

(a) (b)

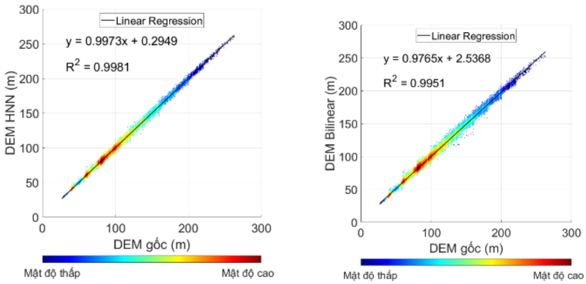


Figure 3.6. Some scatter charts example for the reduced DEM dataset at 20m resolution in Nghe An area

In which: (a)-Scatter chart of DEM after increasing the resolution by HNN and reference DEM; (b)-Scatter chart of DEM is interpolated Bilinear method and referenced DEM.

3.3.2.4. Quantitative evaluation using the Root Mean Square Error (RMSE) value

Table 3.1. Root Mean Square Error value of Bilinear method, Bi-cubic method, Kriging method and Hopfiled Neural Network (HNN) method

Dataset		**Bilinear method**	**Bi-cubic method**	**Kriging method**	**HNN method**	**Improved accuracy compared to Bilinear method**
DEM 20m Nghe An (D1)	Tổng thể	3.3026	3.3716	2.8874	1.9853	**39.9%**
	Min MCD	2.5245	2.5619	2.4393	1.9124	**24.25%**
	Max MCD	3.3379	3.4256	3.2270	2.0171	**39.57%**
	Min MCN	1.3837	1.4051	1.3916	1.5229	**10.06%**
	Max MCN	3.7005	3.7997	3.7522	2.3575	**36.29%**
DEM 30m Nghe An (D2)	Tổng thể	8.8105	8.8736	8.5719	8.3510	**5.21%**
	Min MCD	8.5013	6.8408	6.9101	6.9668	**18.05%**
	Max MCD	11.6961	10.7635	10.8141	11.0702	**5.35%**
	Min MCN	6.6352	6.4032	6.4005	6.2829	**5.31%**
	Max MCN	10.5144	9.8024	9.8357	9.6199	**8.51%**
DEM	Tổng thể	1.5139	1.6000	1.2092	0.8493	**43.90%**

5m Lang Son (S1)	Min MCD	1.1635	1.1821	1.0288	0.5102	**56.15%**
	Max MCD	1.6198	1.7805	1.4232	0.9587	**40.81%**
	Min MCN	1.1567	1.2101	0.7408	0.5897	**49.02%**
	Max MCN	1.6712	1.7451	1.6807	1.1155	**33.25%**
DEM 30m Dac Ha (S2)	Tổng thể	2.3284	2.4218	2.1095	2.0946	**10.0%**
	Min MCD	2.0938	1.0068	1.0624	0.9942	**52.52%**
	Max MCD	4.0702	2.3434	2.4436	2.2330	**45.14%**
	Min MCN	2.8494	1.0181	1.0505	0.9603	**66.29%**
	Max MCN	4.6807	2.3473	2.4070	2.5440	**45.65%**

Evaluation of quantitative accuracy based on the *RMSE* value (Table 3.1) shows that the accuracy of the DEMs after increasing the resolution according to the algorithm using the HNN model is higher than the popular resampling methods: Bilinear, Bi-cubic and Kriging. The *RMSE* value of the DEMs after increasing the resolution was reduced by about 39.9%, 5.2%, 43.9% and 10.0% respectively with the reduced resolution DEMs of 20m and 30m in Nghe An province (datasets D1 and D2), sampled DEM 5m in Lang Son province (dataset S1) and sampled DEM 30m in Dac Ha (dataset S2). The overall *RMSE* values of DEMs after increasing resolution according to HNN model are smaller than those generated by the popular resampling methods: Bilinear, Bi-cubic and Kriging, especially for 5m and 20m DEM datasets.

3.3.2.5. Quantitative assesement using R statistic value (Correlation coefficient) and regression equation (represented by two parameters m and b)

Table 3.2. Linear regression coefficients for all four datasets D1, D2, S1, S2

Datasets		**Linear regression coefficients**		
		m	b	R^2
DEM 20m Nghe An (D1)	The increasing resolution DEM 20m by HNN method	0.9973	0.2949	0.9981
	The resampled DEM 20m by Bilinear method	0.9765	2.5368	0.9951
	The resampled DEM 20m by Bi-cubic method	0.9781	2.3680	0.9948
	The resampled DEM 20m by Kriging method	0.9832	1.8217	0.9962
DEM 30m Nghe An (D2)	The increasing resolution DEM 30m by HNN method	0.9904	-1.6013	0.9686
	The resampled DEM 30m by Bilinear method	0.9500	3.2057	0.9646
	The resampled DEM 30m by Bi-cubic method	0.9529	2.8723	0.9639
	The resampled DEM 30m by Kriging method	0.9608	1.9291	0.9694
DEM 5m Lang Son (S1)	The increasing resolution DEM 5m by HNN method	1.0195	-5.908	0.9937
	The resampled DEM 5m by Bilinear method	0.9601	12.3782	0.9793
	The resampled DEM 5m by Bi-cubic method	0.9658	10.6432	0.9763
	The resampled DEM 5m by Kriging method	0.945	16.3717	0.9884
DEM 30m Dac Ha (S2)	The increasing resolution DEM 30m by HNN method	1.0043	-4.1179	0.9968
	The resampled DEM 30m by Bilinear method	0.9872	12.1453	0.9960
	The resampled DEM 30m by Bi-cubic method	0.9885	10.9118	0.9959
	The resampled DEM 30m by Kriging method	0.9922	7.3917	0.9967

Evaluation values were also performed by linear regression of the spatial resolution of the standard DEM which compared to the increasing resolution using the HNN method and the resampled DEM using standard elevation points, special focus on the coefficients *m*, *b* and R^2 (Table 3.2). Analysis of these parameters showed that the DEMs which after increasing the resolution according to the HNN method are closer to the reference DEMs than the DEMs generated by popular resampling methods.

The results of quantitative assesement were showed that: the method of increasing the spatial resolution of the grid DEM using HNN algorithm gives higher accuracy than the popular resampling methods when running the test on all four datasets.

3.4. Comparison of the accuracy about elevation between the increasing resolution DEMs by Hopfiled Neural Network algorithm and resampling methods with the test elevation points which are measured by electronic total station

To compare the accuracy about elevation values, the author is compared the elevation values of the DEMs after increasing the resolution using the Hopfiled neural network algorithm and the popular resampling methods with the elevation points. Check is measured directly in the field by electronic total station - for the Mai Pha area in Lang Son province. The locations of measuring points (236 measuring points) in the field are illustrated in Figure 3.7.

After spreading the field measurement points with an electronic total station on the grid DEM of the same measurement area on ArcGis software, use the "Extract Multi Value to Point" tool what available in ArcGIS software to extract the elevation values on that DEM at the locations with measuring points to compare the differences between the elevation diffirence measured by electronic total station and the elevation values determined on the DEM (at the same locations).

The results of comparing the difference values of the elevation (calculated according to the absolute elevation values) and the statistics of the errors of the DEMs after increasing the resolution and the field measurement heights were obtained shown in Table 3.3.

Comparing the *RMSE* values of DEMs after increasing resolution by HNN method and Bilinear, Bi-cubic and Kriging methods, we can see that the *RMSE* values of HNN method is the smallest in all researching methods. It means that the accuracy of the method using the Hopfiled Neural Network model is highest.

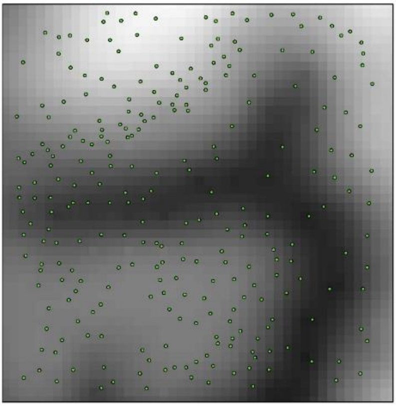


Figure 3.7. Spread the actual measuring points onto the 5m Lang Son DEM

Table 3.3. Statistics table of elevation value differences, errors between DEMs increasing the resolution and measuring points by electronic total station

	DEM HNN	**DEM Input**	**DEM Bilinear**	**DEM Bi-cubic**	**DEM Kriging**
Max (m)	3.637	7.240	4.878	5.076	3.609
Min (m)	0.001	0.000	0.000	0.000	0.000
Mean (m)	0.783	1.786	1.168	1.208	0.957
RMSE (m)	**1.097**	**2.378**	**1.518**	**1.623**	**1.190**

3.5. Conclusion chapter 3

In this chapter proposed a new method to increase the spatial resolution and accuracy of grid DEMs and experiment, assess with different parameters using the DEM datasets with resolution and different characteristics. The proposed new resolution increase algorithm is built on a Hopfield neural network (HNN) with the objective function of maximizing spatial dependence and constrained elevation. The experimental results show that the accuracy of the DEM which increased spatial resolution using HNN method is much higher than the popular resampling methods: Bilinear, Bi-cubic and Kriging.

The visual and quantitative assessment has shown that DEMs spatial resolution increase algorithm using HNN method performs more accurately for some typical topographic characteristics such as valley bottom or peaks of mountain ranges. This improvement can be considered due to the effect of the height constraint on the spatial dependence maximization functions in this HNN algorithm. That is, the typical method of using the HNN method offers a structural advantage when increasing the resolution of DEM, which is not possible with current popular spatial interpolation and popular resampling methods.

CONCLUSIONS AND RECOMMENDATIONS

A. Conclusions

The research results of this thesis have confirmed and proved the scientific hypothesizes, from which gives the conclusions:

1. In the thesis, a new approach for grid DEM accuracy assessment using a combination of regression parameters (m, b) when building a linear correlation relationship between standard data, comparison data and correlation coefficient R was proposed. The simultaneous using of the these parameters enables the discovering the evidence of random and systematic errors in DEMs.

2. The accuracy assessment using linear regression parameters (m, b) and the correlation coefficient R showed that the conventional resampling algorithms such as Bilinear, Bi-cubic, especially the Kriging method, can be used to improve the accuracy of the grid DEMs. However, the analysis also showed that these algorithms caused a certain amount of systematic errors in the resulted downscaled DEM due to the smoothing effect. The elevation values of the downscaled DEMs using these approaches tend to be lower at the tops of the hills, mountains and hydrolysis peaks as well as higher at valley bottom or precipitation points.

3. The thesis proposes a new method to improve the accuracy of grid DEM data using downscaling model based on Hopfield neural network. This new approach can improve accuracy of the grid DEM compared to other conventional resampling methods. This accuracy enhancement model is the combination of smoothing DEM through the target function defined by the *semi-variance* minimization and the elevation constraint function. The accuracy assessment based on visual and statistical approaches showed that the proposed method outperforms the conventional resampling approaches such as Bilinear, Bi-cubic and Kriging in downscaling grid DEMs, especially in the at the tops of the hills, mountains and hydrolysis peaks as well as higher at valley bottom or precipitation points due to the effect of elevation constraint.

B. Recommendations

1. Based on the results of the algorithm, the author wishes to continue to be supported to be able to build software modules that allow the application of the HNN algorithm in practice to improve the accuracy of DEMs and similar elevation data.

2. The research continues to improve the algorithm, in which will built the soft elevation constraint function, allowing the errors existing in the DEM input to be eliminated.

3. Research to expand the algorithm when there are additional sources of information that can assist in adjusting the elevation values of the new model, or allow mixing of different elevation data sources to create a higher accuracy DEMs than the original DEMs, sufficiently accurate for the fields where the DEM is used such as landslide researches, hydrological flow modeling, etc.

LIST OF SCIENTIFIC WORKS PUBLISHED BY AUTHORS RELATING TO THE THESIS CONTENTS

A. Scientific projects:

1. Chủ trì đề tài cấp cơ sở (2018): "Nghiên cứu nâng cao độ chính xác của mô hình số độ cao dạng grid bằng phương pháp sử dụng mạng nơ ron Hopfiled", Trường Đại học Mỏ - Địa chất. Mã số T18-11.

B. Articles /Scientific report:

Vietnamese

1. Nguyen Thi Thu Huong (2018), "Một cách tiếp cận mới nhằm tăng độ phân giải không gian của mô hình số độ cao dạng grid bằng phương pháp sử dụng mạng nơ ron Hopfield.", Kỳ yếu hội thảo khoa học Trái đất – Mỏ - Môi trường bền vững (EME 2018), p. 238-246, ISBN: 978-604-913-687-0.

2. Nguyen Thi Thu Huong (2019), "Một phương pháp nhằm tăng độ phân giải không gian của mô hình số độ cao dạng grid sử dụng mạng nơ ron Hopfiled", Tạp chí Khoa học Kỹ thuật Mỏ - Địa Chất, Tập 60, kỳ 2, ISSN 1859-1469.

English

3. Nguyen Thi Thu Huong, Nguyen Quang Minh (2018), "Comparison of the resampling methods for gridded dem downscaling", Tạp chí Khoa học Kỹ thuật Mỏ - Địa Chất, Số tiếng Anh, tập 59, kỳ 6, ISSN 1859-1469.

4. Nguyen Quang Minh, Nguyen Thi Thu Huong, La Phu Hien, Hugh Lewis, P. Atkinson (2018), "Downscaling gridded DEM using the Hopfield Neural Network", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, ID JSTARS-2018-00862.

5. Nguyen Quang Minh, Nguyen Thi Thu Huong (2013), "Increasing Spatial Resolution of Remotely Sensed Image using HNN Super-resolution Mapping Combined with a Forward Model", Journal of the Korean of Surveying, Geodesy, Photogrammetry and Cartography, Vol.31, No. 6-2, 559-565, ISSN 1598-4850(Print), ISSN 2288-260X (Online).

6. Nguyen Quang Minh, Nguyen Thi Thu Huong, La Phu Hien, Duong Thi Tuyet Nhung (2019), "Comparison of the conventional resampling methods for gridded DEM downscaling", Journal of the Polish Mineral Engineering Society Pol-Viet 2019, Doi: http://doi.org/10.29227/IM-2019-01-77.

7. Nguyen Quang Minh, Nguyen Thi Thu Huong, La Phu Hien, Pham Thanh Thao, P.M. Atkinson (2016), "Increasing the Grid DEM Resolusion Using Hopfield Neural Network, A Test For Data in LangSon Province, VietNam", International symposium on Geo-Spatial and Mobile mapping technologies and summer school for Mobile mapping technology (GMMT2016), ISBN 978-604-76-914-4.

8. Nguyen Quang Minh, Nguyen Thi Thu Huong, La Phu Hien (2016), "A Quantitative Assessment of Algorithm for Increasing Gridded DEM resolution using the Hopfield Neural Network", International Conference on Earth Sciences And Sustainable Geo-Resources Development (ESASGD 2016), ISBN 978-604-76-1171-3.