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Research Article

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Image Processing on Ruins of Hitite Civilization Using Random Neural Network Approach

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Abstract Geophysical methods have been widely used in recent years to display, model and uncover buried archaeological artifacts. In line with the information received from the archaeologists, it is decided which geophysical methods should be used in the archaeological structures to be searched. Thus, as a result of the studies, we can have information about the location and location of the archaeological work. In this way, we can direct the archaeological excavation and make the excavation to the depth where the artifact can be found without damaging the archaeological artifact and determine the limits of archaeological artifacts. In this paper, Random Neural Network (RNN) has been applied to a real archaeological magnetic map belonging to ancient Hittite civilization, obtained by an international research group. RNN is a contemporary, stochastic approach for 2-D image processing for real-time models. The domain-dependent prior knowledge, such as the sizes, the shapes, the depth and the orientations of observed regions can be reflected in the parameters of RNN structure. We have separated regional and residual anomalies of Hittite civilization using RNN and extracted the historical Sarissa -Kusakli walls close to Sivas city in Turkey. We have shown that the performance of RNN is better than classical derivative based techniques.

Keywords Random Neural Network (RNN), archaeological study, magnetic, Hittite civilization

Introduction

Egyptian and Mesopotamia civilizations are well known while Hittite (BC. 1660-1190) has attracted the scientist mostly at the last decades. Even the famous historian Heredot had commented the wall graphics of Hittite as Egyptian. After 19^{th} century, the archaeological studies have enlightened Hittite civilization and it is found out that Hittite Empire was established in the Eastern part of Turkey (Figure 1). The study area is located just east of Deliyusuf village in Sivas-Altınyayla region (Figure 2). In 1992, after the surveys carried out in the Hittite city ruins in the Kuşaklı region of Sivas province, Altınyayla district, the first excavations were started in 1993 and the studies are still continuing today.

In recent years, geophysical methods are widely used for the search of archaeological remains. He made studies on why GPR (Ground-penetrating Radar) is important in archaeological research [3]. They conducted resistivity, magnetic and GPR studies in the discovery of archaeological sites in northern Greece [4]. The Hittite empire period [5] in the Külhöyük region. They carried out studies in the Sivas-Belt zone [6,7,8,9,10,11,12,13].

Figure 1: General information about Hittite civilization [1].

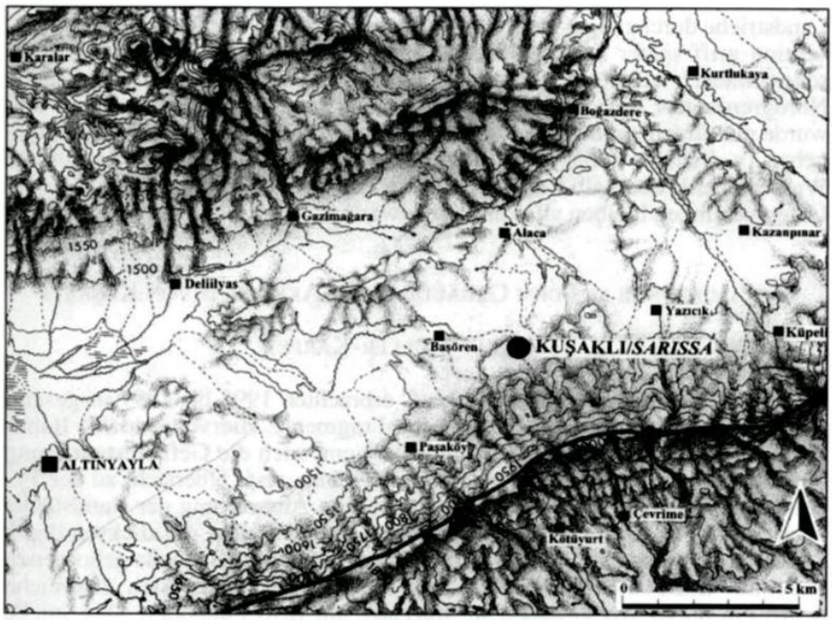

Figure 2: The ancient cities of Hittite including Kusakki-Sarıssa [2]

Method

Random Neural Network (RNN) model have defined in 1989 and extended and generalized in 1990 by [14 and 15]. In RNN model, there are positive and negative signals. These signals, which are in the form of spikes of unit amplitude, circulate among the neurons. Positive signals represent excitation and negative signals represent inhibition. These signals can arrive either from other neurons or from outside world. They are summed at the input of each neuron and constitute its signal potential. Each neuron's state is a non-negative integer number called its potential, which increases when an excitation signal arrives to it, and decreases when an inhibition signal arrives. Thus, an excitatory spike is interpreted as a ``+1" signal at a receiving neuron, while an inhibitory spike is interpreted as a ``-1" signal. If neuron potential is positive, it fires and sends out signals to the other neurons of the network or outside world. Neural potential also decreases when the neuron fires. Thus a neuron emitting a spike, whether it is an excitation or an inhibition, will lose potential of one unit, going from some state to previous state (Figure 3).

The state of the n-neuron network at time t, is represented by the vector of non-negative integers $k(t) = (k_1(t),\ldots,k_n(t))$, where $k_i(t)$ is the potential or integer state of neuron i. Arbitrary values of the state vector and of the i-th neuron's state are shown by k and k_i. Neuron i fires (i.e. become excited and send out spikes) if its potential is *positive*. The spikes are sent out at a rate $r(i)$, with independent, identically and exponentially distributed inter-spike intervals. Spikes go out to some neuron j with probability $p^+(i,j)$ as excitatory signals, or with probability $p^-(i,j)$ as inhibitory signals. A neuron may also send signals out of the network with probability $d(i)$. There is a relationship between these probabilities as follows;

$$d(i) + \sum\left[p^+(i,j) + p^-(i,j)\right] = 1 \qquad (1)$$

If we show weights between neurons with ω^+ and ω^-, they calculate as follows;

$$\omega^+_{ij} = r(i)p^+(i,j), \quad \omega^-_{ij} = r(i)p^-(i,j) \qquad (2)$$

These ω's similar to synaptic weights in connectionist models. Exogenous (i.e. those coming from the ``outside world") excitatory and inhibitory signals also arrive to neuron $i$ at rates $\Lambda(i)$, $\lambda(i)$, respectively. This is a ``recurrent network" model, *i.e.* a network, which is allowed to have feedback, loops, of arbitrary topology.

Computations related to this model are based on the probability distribution of network state $p(k,t) = \Pr[k(t) = k]$, or with the marginal probability that neuron i is excited $q_i(t) = \Pr[k_i(t) > 0]$. As a consequence, the time-dependent behavior of the model is described by an infinite system of *Chapman-Kolmogorov* equations for discrete state-space continuous Markovian systems.

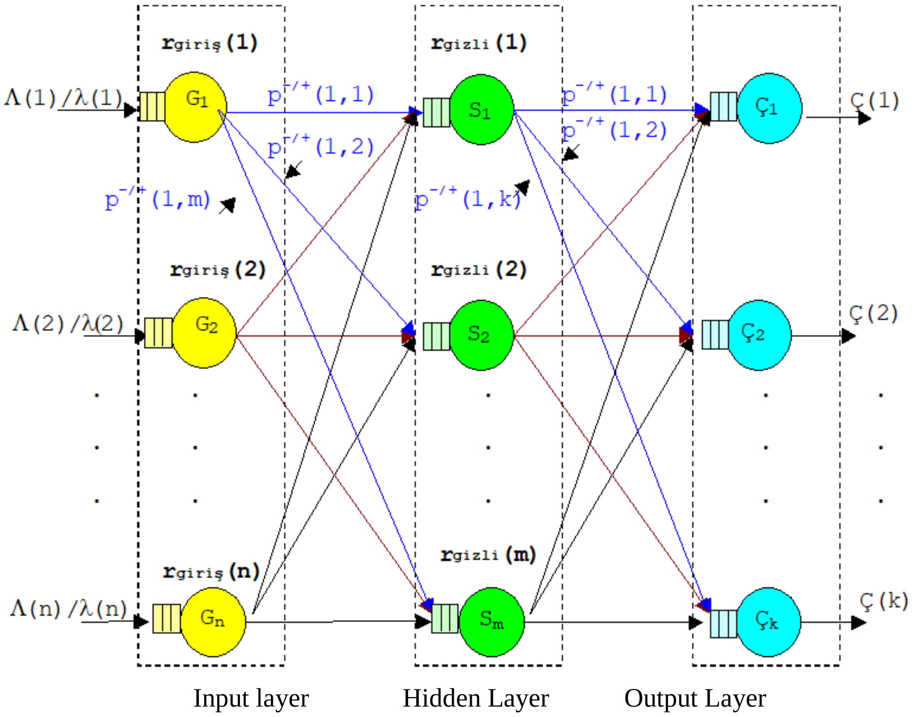

Figure 3: Random Neural Network model [16]

Information in this model is carried by the *frequency* at which spikes travel. Thus, neuron j, if it is excited, will send spikes to neuron i at a frequency $\omega_{ij} = \omega_{ij}^+ + \omega_{ij}^-$. These spikes will be emitted at exponentially distributed random intervals. In turn, each neuron behaves as a non-linear *frequency demodulator* since it transforms the incoming excitatory and inhibitory spike trains' rates into an ``amplitude", which is $q_i(t)$ the probability that neuron i is excited at time t. Intuitively speaking, each neuron of this model is also a frequency modulator, since neuron i sends out excitatory and inhibitory spikes at rates (or frequencies) $q_i(t)r(i)p^+(i,j)$, $q_i(t)r(i)p^-(i,j)$ to any neuron j.

The stationary probability distribution associated with the model is the quantity used throughout the computations:

$$p(k)=\lim_{t\to\infty} p(k,t),\ q_i=\lim_{t\to\infty} q_i(t),\ i=1,2,..,n \tag{3}$$

It is given by the following result:

Theorem 1. *Let q_i denote the quantity*

$$q_i=\lambda^+(i)/[r(i)+\lambda^-(i)] \tag{4}$$

Where the $\lambda^+(i),\lambda^-(i)$ for $i = 1,...,n$ satisfy the system of nonlinear simultaneous equations:

$$\lambda^+(i)=\sum_j q_j r(j)p^+(i,j)+\Lambda(i),\qquad \lambda^-(i)=\sum_j q_j r(j)p^-(i,j)+\lambda(i) \tag{5}$$

Let $k(t)$ be the vector of neuron potentials at time t and $k=(k_1, \dots, k_n)$ be a particular value of the vector; let $p(k)$ denote the stationary probability distribution;

$$p(k)=\lim_{t\to\infty}\Pr[k(t)=k]$$

If a nonnegative solution { $\lambda^+(i),\lambda^-(i)$ } exists to equations (4) and (5) such that each $q_i<1$, then

$$p(k)=\prod_{i=1}^{n}[1-q_i]q_i^{ki} \tag{6}$$

The quantities, which are most useful for computational purposes, *i.e.* the probabilities that each neuron is excited, are directly obtained from:

$$\lim_{t\to\infty}\Pr[k_i(t)>0]=q_i=\lambda^+(i)/[r(i)+\lambda^-(i)] \quad \text{if} \quad q_i<1.$$

For notational convenience following is written;

$$\omega^+(j,i)=r(i)p^+(i,j)\ge 0,\qquad \omega^-(j,i)=r(i)p^-(i,j)\ge 0$$

$$N(i)=\sum_j q_j\omega^+(j,i)+\Lambda(i),$$

$$D(i)=r(i)+\sum_j q_j\omega^-(j,i)+\lambda(i)$$

Then equation 4 becomes

$$q_i=\frac{N(i)}{D(i)}$$

and

$$r(i)=\sum_j\left[\omega^-(j,i)+\omega^+(j,i)\right].$$

We can represent this neural network model as shown Figure 1. Actually there isn't any different from other network. Different things that there are two weights between two neurons (ω^+,ω^-). Unless neuron potential is positive, neuron doesn't join to calculate. Thus this network model similar to a type of genetic algorithm.

In addition to RNN can be implemented in hardware as shown in Figure 4. Each neuron is represented by a counter and a Random Number Generator (RNG). To simulate the exponential delays associated with the signal emission, RNG is used. The interconnection network receives signals from counter RNG represents each neuron. Signals can be viewed as short packets of data containing the signal's polarity and its destination. And interconnection network routes the signal to the appropriate output line to the neuron to which it is addressed.

The Learning Algorithm

Learning algorithm of RNN is based on the algorithm described in [14]. The algorithm chooses the set of network parameters (ω^{+}, ω^{-}) in order to learn a given set of *K* input-output pairs (*i* , Y) where the set of successive inputs is denoted , $i = \{i_1, ..., i_k\}$ and $i_k = (\Lambda_k, \lambda_k)$ are pairs of positive and negative signal flow rates entering each neuron:

$$\Lambda_k = [\Lambda_k(1), ..., \Lambda_k(n)], \qquad \lambda_k = [\lambda_k(1), ..., \lambda_k(n)]$$

The successive desired outputs are the vectors, where each vector , whose elements correspond to the desired values of each neuron. The network approximates the set of desired output vectors in a manner that minimizes a cost function. If we wish to remove some neuron *j* from network output, and hence from the error function, it suffices to set *Both* of the *n* by *n* weight matrices and have to be learned after each input is presented, by computing for each input , a new value and of the weight matrices, using gradient descent. Clearly, we seek only solutions for which all these weights are positive. Let *w*(*u*,*v*) denote any weight term, which would be either. The weights will be updated as follows: where is some constant, and

1. is calculated using the input and , in Equation 3.
2. is evaluated at the values and .

To compute we turn to the expression 3, from which we derive the following equation. We now have the information to specify the complete learning algorithm for the network. We first initialise the matrices and in some appropriate manner. This initiation will be made at random. Choose a value of, and then for each successive value of *k*, starting with *k* = 1 proceeds as follows:

1. Set the input values to 0
2. Solve the system of non-linear equations 3 with these values.
3. Solve the system of linear equations (8) with the results of (2).
4. Using equation (7) and the results of (2) and (3), update the matrices and . Since we seek the ``best'' matrices (in terms of gradient descent of the quadratic cost function) that satisfy the *nonnegative* constraint, in any step *k* of the algorithm, if the iteration yields a negative value of a term, we have two alternatives:
    1. Set the term to zero, and stop the iteration for this term in this term in this step *k*; in the next stop *k*+1 we will iterate on this term with the same rule starting from its current null value;
    2. Go back to the previous value of the term and iterate with a smaller value of.

This general scheme can be specialized to feed forward networks yielding a computational complexity of , rather than , for each gradient iteration.

Application of Random Neural Network for Sarissa-Kusaklı Region

Geophysical maps usually contain a number of features (anomalies, structures, etc.) which are superposed on each other. The aim of an interpretation of such maps is to extract as much useful information as possible from the data. Since one type of anomaly often masks another, the need arises to separate the various features from each other. In this section, gravity and magnetic fields are to be investigated.

Traditionally, magnetic and gravity maps are subjected to operations approximating certain functions such as second derivative and downward continuation. Gravity data observed in geophysical surveys are the sum of gravity fields produced by all underground sources. The targets for specific surveys are often small-scale structures buried at shallow depths, and these targets are embedded in a regional field that arises from residual sources that are usually larger or deeper than the targets or are located farther away. Correct estimation and removal of the regional field from initial field observations yields the residual field produced by the target sources. Interpretation and numerical modelling are carried out on the residual field data, and the reliability of the interpretation depends to a great extent upon the success of the regional-residual separation.

In literature some classical methods are proposed for the separation of gravity maps. The simplest is the graphical method in which a regional trend is drawn manually for profile data. Determination of the trend is based upon interpreter's understanding understanding of the geology and related field distribution. This is a subjective approach and also becomes increasingly difficult with large 2-D data sets. In the second approach,

the regional field is estimated by least-squares fitting a low-order of the observed field [17]. This reduces subjectivity, but still needs to specify the order of the polynomial and to select the data points to be fit. The third approach applies a digital filter such as Wiener filtering to the observed [18]. In recent years, there are many inter-discipline studies on image processing of geophysical data using update electronics techniques. They conducted geophysical studies in the archaeological sites of the Hittite civilization [19,20,21,22,23].
In our considered Sarissa-Kusakli archeological region which lies close to Sivas city in Turkey, there are many researches. They carried out archaeological and geophysical studies belonging to the Hittite civilization in the belt Sarissa region [6,7,8,9,10]. In this paper, we have evaluated the magnetic map of Sarissa-Kusakli region and separated residual anomaly using Random Neural Network (RNN) method.

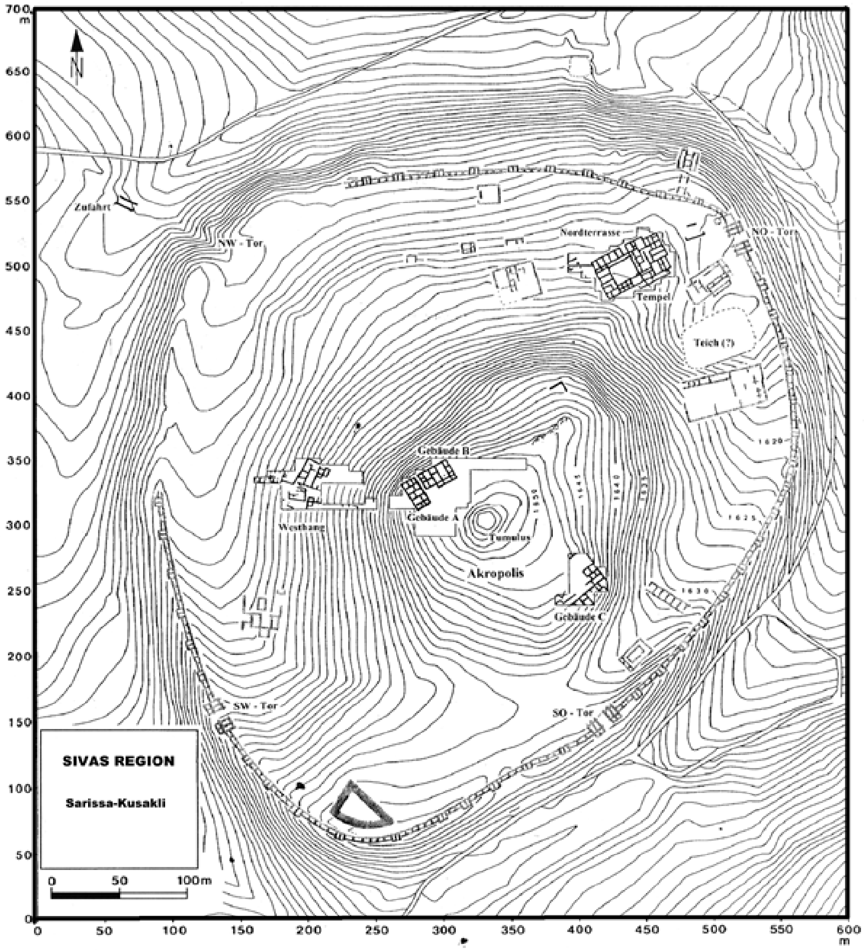

Figure 4: Topography map including excavation results [24].

Geological structure of the research area

The investigated area is situated in the south and southeast of Sarkisla (Sivas), in which formations of Upper Cretaceous- Paleocene, Eocene, Oligocene and Pliocene ages crop out. While Upper Cretaceous- Paleocene is represented by turbiditic limestone intercalated with tuff, Tuffite, volcanic sandstone and lavas, Eocene is only represented by conglomerate and clayey limestone. Both of them are in marine origin. Oligocene is composed of lagunar gypsium and lacustrine sandstone, conglomerate, and marls. As for to Pliocene is also represented conglomerates, clayey limestone and basalts in terrestrial origin. Ophiolitic melange occurrences forming the basement in the study area have been emplaced by gravity slides in the form of olistostromes into th sediments as separated sheets from Paleocene up to the end of middle Eocene. Volcanoclastics, turbiditic limestone, the secondary emplacement of the ophiolitic melange in the form of olistostromes and the geochemical character of volcanism indicate that the study area has been developed as a kind of rear-arc basin during Paleocene time.

Field study of Random Neural Network (RNN) method

The considered historical region, Sarissa-Kusakli lies close to Sivas-Altınyayla Başören village (Figure 2). After the correlation between Hittite and Indo-German societies are found out, European countries tended to this archeological civilization. The first studies dated as 1832 and since 1932, Deutsche Archäologische Gesellschaft is supporting the archeological researches.

In Hattusas documents, 1600 different dwellings are being reported but nowadays only 12 of them is enlightened. Sarissa as being one of the most important historical city of Hittite civilization, has attracted many scientists. The city was established at about BC 1600 and at that time governed by a local King. After a great fire, the city was left and in BC 700-800, it was again gained power. The aim of the researches is to find out better information on this civilization and their political, regional effects on the following Anatolian cultures. In Figure 4, the topological map of Sarissa-Kusakli Region is given.

The wall of the city with 1.5 km length and 18 hectare area, surrounds the old city. The excavation of Sarissa is still continuing by German, French, Canadian and Turkish scientists. Fluxgate (Fluxgate-Gradientsonden-Array, Type Foerster) instrument and Fluxgate-Gradient drilling measurement equipment are being used in these studies (Figure 5). Drilling distance space is 0.4 meter and drilling depth is 30-40 cm. Measurements are taken at each 0.1 m.

Figure 5: Kuşaklı-Sarissa region using Flux-gate magnetometers [19]

In archaeological studies, it is tried to estimate the buried structures close to the surface. In this study, we applied RNN for magnetic anomaly map (Figure 6a) using Fluxgate-Gradientsonden-Array tool on the remains of the Hittite civilization. Residual anomaly map was obtained by applying RNN method to the magnetic anomaly map obtained (Figure 8). By applying boundary analysis method to the obtained magnetic anomaly map, boundary analysis in figure 6b was obtained. Again, the second vertical derivative of Haalck was applied to the obtained magnetic anomaly mortar. Figure 6c was obtained. Finally, residual anomaly map was obtained by applying RNN method to magnetic anomaly map (Figure 6d). The RNN outputs obtained were compared with the classical derivative-based approach (Figure). We have shown that the performance of the RNN method has yielded better results than conventional methods. The excavated historical walls of the area under consideration are shown in Figure. The walls are horizontal and long as in RNN exit.

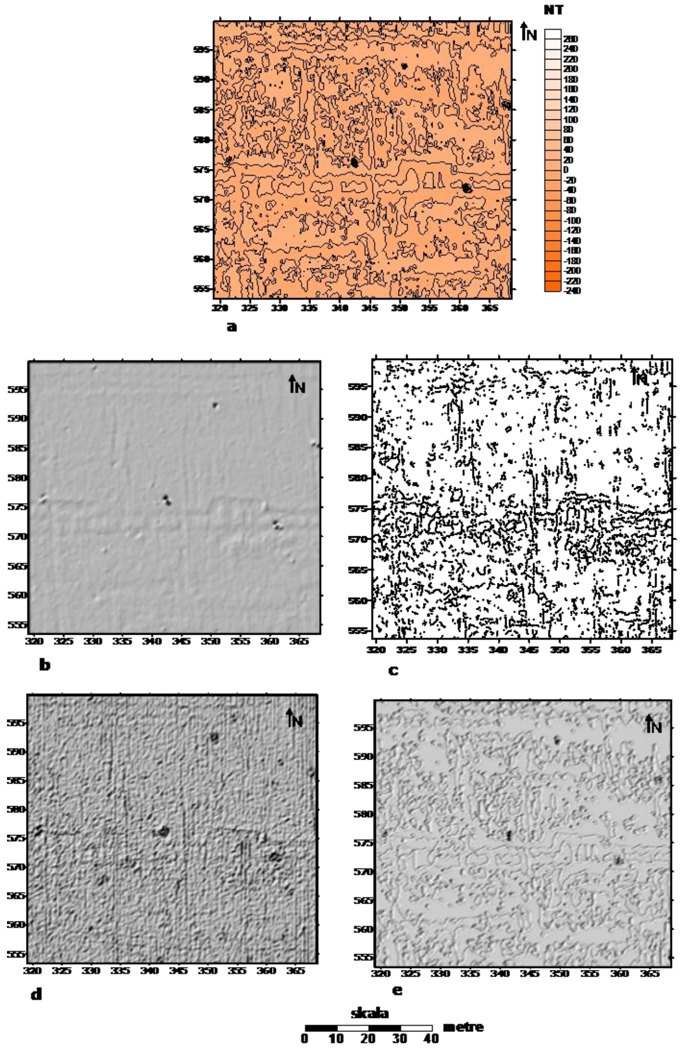

Figure 6: The remains of the Hittite civilization a- Study site magnetic anomaly map. b- Relief output of the magnetic map. c- Result of boundary analysis of magnetic anomaly map d- Second vertical derivative output of magnetic anomaly map. Map obtained after applying the RNNA method

Conclusion

In archaeogeophysical studies, it is aimed to reveal symptoms close to the surface. Archaeologists make effective use of geophysical methods to reveal archaeological remains. Recently, image processing methods in electronic engineering have been used to transform archeogeophysical data into images. This study aimed to Altınyayla-Turkey Hittite empire in eliciting residue. The area covering the 550-600 longitude and the 310-370 latitude selected in the western part of the archaeological site of the Hittite civilization was chosen as the application area. The dimensions of the total working area are 95 * 85 m2. Magnetic anomaly map was obtained on the historical walls of Hittite civilization (Figure 6a). In addition, the boundary analysis method and the second vertical derivative of Haalck were compared to the magnetic anomaly map obtained in this region (Figure 6b and 6c). Random Neural Network (RNN) method, one of the image processing methods, was applied to the magnetic anomaly map obtained on the archaeological structures of the Hittite civilization (Figure 6d). As a result of the studies, we see that RNN method reveals the archaeological building walls very clearly. After the magnetic anomaly maps were evaluated, historical walls were revealed as a result of the studies carried out by archaeologists (Figure 7).

Figure 7: The historical wall of Sarissa acropolis

Acknowledgments

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