

ITERATIVE CELLULAR IMAGE PROCESSING ALGORITHM*

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ABSTRACT

In this paper, a new iterative image processing algorithm is introduced and denoted as “iterative cellular image processing algorithm” (ICIPA). The new unsupervised iterative algorithm uses the advantage of stochastic properties and neighborhood relations between the cells of the input image. In ICIPA scheme; first regarding to the stochastic properties of the data, all possible quantization levels are determined and then 2D input image is processed using a function, based on averaging and neighborhood relationship, and after that a parameter C is assigned to each cell. Then Gaussian probability values are mapped to each cell regarding to all possible quantization levels and the attended value C. A maximum selector defines the highest probability value for each cell. In the case of complex data, first iteration output is fed into input till a sufficient output is found.

We have applied ICIPA algorithm to various synthetic examples and then a real data, the ruins of Hittite Empire. Satisfactory results are obtained. We have observed that de-noising property of our scheme is the best in the literature. It is interesting that the corrupted data with Additive White Gaussian Noise (AWGN) up to 97% ratio, can be de-noised by using our proposed ICIPA algorithm.

Keywords: *Iterative Cellular Image Processing, de-noising, archeological ruins.*

1. INTRODUCTION

Geophysical methods are being commonly used nowadays in the evaluation of archeological buried objects. There are many studies on archeological areas. Vaughan in [1] used Ground-penetrating radar in

archeological sites. Tsokas et al worked in North of Greece using geophysical methods in [2]. Drahor focused on Halikarnasus antic city in [3], Sayın evaluated Tekirdağ-Menekşe region by magnetic and SP approaches in [4], Akçığ and Pınar studied on Bandırma-Kösemtuğ tomb in [5], Ercan and Temizsöz on

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Hattusa Hittite Empire in [6]. Candansayar et al used inverse resistivity techniques and found out Hittite ruins in [7]. Ercan worked on Eđmir Hellenistic period tombs in [8]. Bilgili explained the importance of georadar, geo-electric, geo-magnetic approaches in [9]. Wavelet is first applied to geophysics by Fedi and Quata in [10]. Ucan et al have separated residual/regional data using wavelet approach in [11,12]. Albora et al have applied Cellular Neural Network in [13,14], which was introduced in [15] by Chua and Yang, for geophysics and found out the borders of iron ore in Dumluca, Turkey. All these geophysical investigations have helped the archeologist to enlighten the human history.

In this study, we focused on ruins of Hittite Empire in Sivas-Altınyayla Kusaklı region in Turkey. As shown in Figure 1, Hittite civilization has been spread all over the Anatolian. Sivas-Altınyayla Kusaklı is the first found city of Hittite by chance. Hittite society settled in Anatolia in the second century B.C. There are many researches using methods such as magnetic, resistivity, georadar in [16-19]. It is found that there has been an important burning of the cities resulting magnetic property. In Kusaklı, a tablet is found with sa ra/ia-ia-sa words on it, meaning that the city belongs to King of Hittite by Müller-Kerpe. Finally, Hittite Empire city boarder in Sivas-Altınyayla Kusaklı region is well defined with Iterative Cellular Image Processing Algorithm by Osman et al [20].

We have processed magnetic anomalies of Kusaklı region. We proposed a new compromising algorithm denoted as "iterative cellular image processing algorithm (ICIPA). The new unsupervised algorithm is an iterative algorithm which uses the advantage of stochastic properties and neighborhood relations of the input data. In ICIPA scheme, in the first iteration, regarding to the stochastic properties of the data, all possible quantization levels are determined. 2D input image is processed using a function, based on averaging and neighborhood relationship and a parameter C is attended for each cell. Then Gaussian probability values are mapped for each cell regarding to all possible quantization levels and the attended value C. A maximum

selector defines the highest probability value for each cell. In the case of complex data, first iteration output is fed into input till a sufficient output is found (Figure 2).

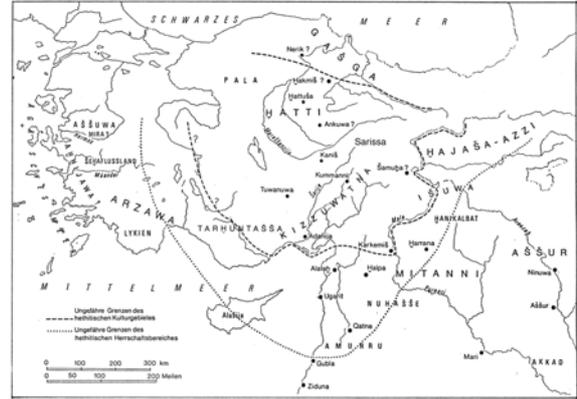


Figure 1. Hittite Civilization in Anatolia.

2. ITERATIVE CELLULAR IMAGE PROCESSING ALGORITHM

This algorithm has iterative and cellular characteristics. Figure 2 shows the block diagram of proposed restoration algorithm. Here there are four blocks and one switch. At the very first iteration, switch is in up position, but for all other iterations the switch is in down position.

In the first block, neighborhood parameter C matrix is computed. For a cell the C_{ij} the output values of the neighbor cells are multiplied by some weights, summed then averaged according to the weights whereas the output of the cell C_{ij} is multiplied by 1. This can be formulized as,

$$C_{i,j}^{(t)} = \frac{1}{\left(1 + \sum_{z=1}^m \frac{8}{z}\right)} \sum_{k=i-m}^{i+m} \sum_{l=j-m}^{j+m} \left(\frac{1}{\text{Max}(|k-i|, |l-j|)} \right)^2 \cdot C_{k,l}^{(t-1)} \quad (1)$$

here i and j are row and column indexes, t is iteration index, m is the level of neighborhood which effects the cell and maximum is an operator which finds out the maximum of the values in the parentheses in the case of the conditions given below.

$$Max(|k-i|, |l-j|) = \begin{cases} |k-i| & \text{if } |k-i| \geq |l-j| \text{ and } |k-i| \neq 0, \\ |l-j| & \text{if } |l-j| \geq |k-i| \text{ and } |l-j| \neq 0, \\ 1 & \text{if } |k-i| = |l-j| = 0, \end{cases} \quad (2)$$

m can take any integer value and this designates the template dimensions. For m=3 template is shown in Figure 3. At the first iteration t=1 and C^(t-1) indicates the cells of the input image. Effect of the neighborhoods w_z, decreases when the level of neighborhood increases and this effect can be shown as,

$$w_z = \left(\frac{1}{z}\right)^2, \quad z=1 \dots m \quad (3)$$

and w₀, shows the loop of itself and it is 1. We cannot use (1) completely for every cell, since if the C_{ij} is close enough to the border of the image, the neighborhood level overflows and frames of the neighborhoods is quite different than template. In this type of border conditions, common parts of the template and image are considered and weighted average is computed.

Before calculating the color probability of the cells, quantization levels are obtained from the image according to the color level. These quantization levels are chosen from the colors which are encountered in the image. To calculate the color probability of the cells, we use logarithmic form of Gaussian probability density function.

$$Pr(C_{i,j}^{(t)} = q_l) = -\frac{(C_{i,j}^{(0)})^2}{2\sigma^2} - \frac{(C_{i,j}^{(t)} - q_l)^2}{2\sigma^2} \quad (4)$$

Here l is quantization index, q_l shows the quantization or color level and σ² is the variance of the noise. Calculation of the variance of the noise is very easy for synthetic data but not so easy for real data.

After computing the color probabilities of the cells, a maximum selector is applied. Most probable color is chosen from the quantization levels according to the color probabilities which are given in Equation 4.

In this new method, the object size and template size are very correlated with each other. Thus, choosing the template level and the object size that we are trying to find out is very important and can be given as,

$$\frac{\text{number of pixel in the template}}{\text{number of pixel in the object}} \quad (5)$$

In simulations, we add Gaussian noise to synthetic data. We indicate noiseless real data as x_{ij} and noisy data as C_{ij}. Noisy data can be shown as,

$$C_{i,j} = x_{i,j} + n_{i,j} \quad (6)$$

here n_{ij} is Gaussian noise. Additional noise in percentage can be calculated as,

$$n_p = \sqrt{\frac{\sum_i \sum_j (x_{i,j} - C_{i,j})^2}{\sum_i \sum_j x_{i,j}^2}} \quad (7)$$

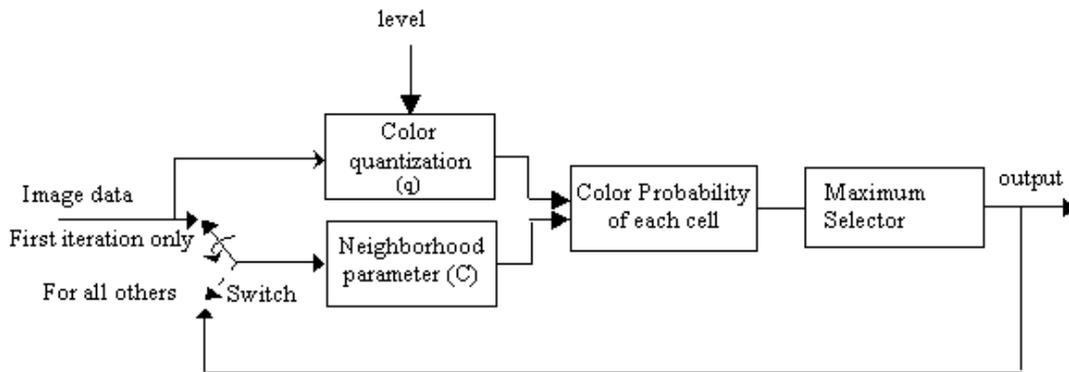


Figure 2. Iterative-Cellular Image Processing Algorithm block diagram.

3. Simulation Results

3.1. Synthetic Examples

Our ICIPA method has been first applied to synthetic examples of magnetic data as shown in Figure 4a. In the first example, the input magnetic data is corrupted by and addition of 92% of Additive White Gaussian Noise (AWGN).

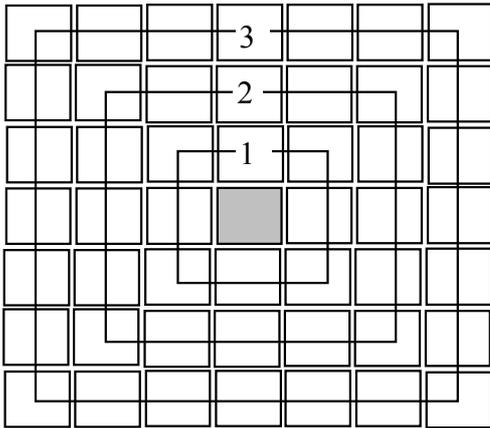
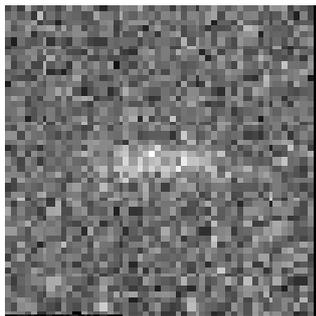


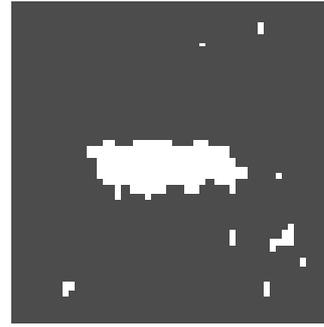
Figure 3. Neighborhood relations (template) for $m=3$.



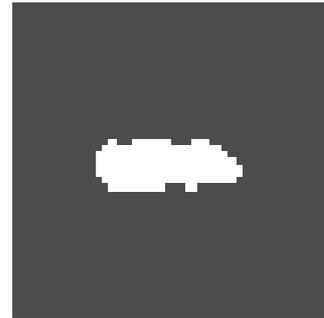
a



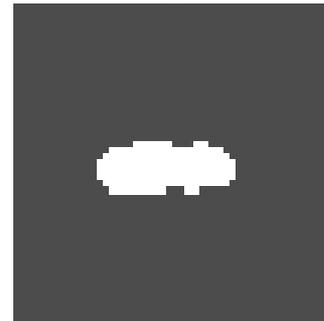
b



c



d

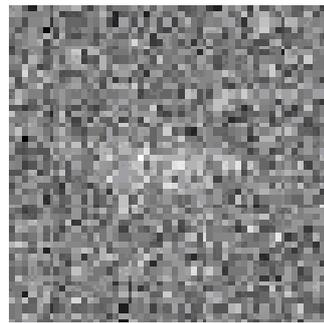


e

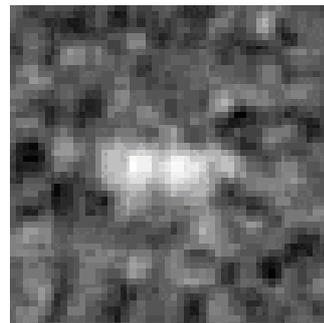
Figure 4. (a) Input image of a magnetic data composed of a prism (b) 92% noise added form of the input data (c) ICIPA output for first iteration, neighborhood level $m=2$ and quantization level $q=2$ (d) ICIPA output for third iteration, neighborhood level $m=2$ and quantization level $q=2$ (e) ICIPA output for fifth iteration, neighborhood level $m=2$ and quantization level $q=2$

We have added 92% Gaussian noise as in Figure 4b. The de-noising of such a extra noised data is impossible using algorithms in the literature. It is very interesting that our approach is capable of de-noising as in Fig. 4c-e for different iteration numbers, neighborhood relations, and quantization

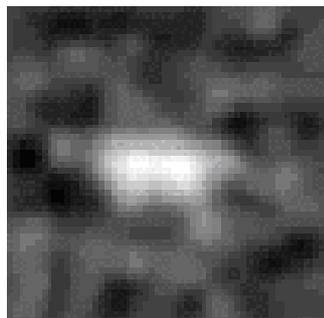
levels. In the second example, the noising effect is increased up to %97 as in Figure 5.



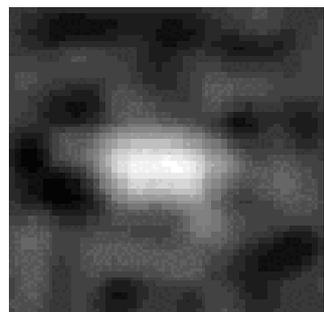
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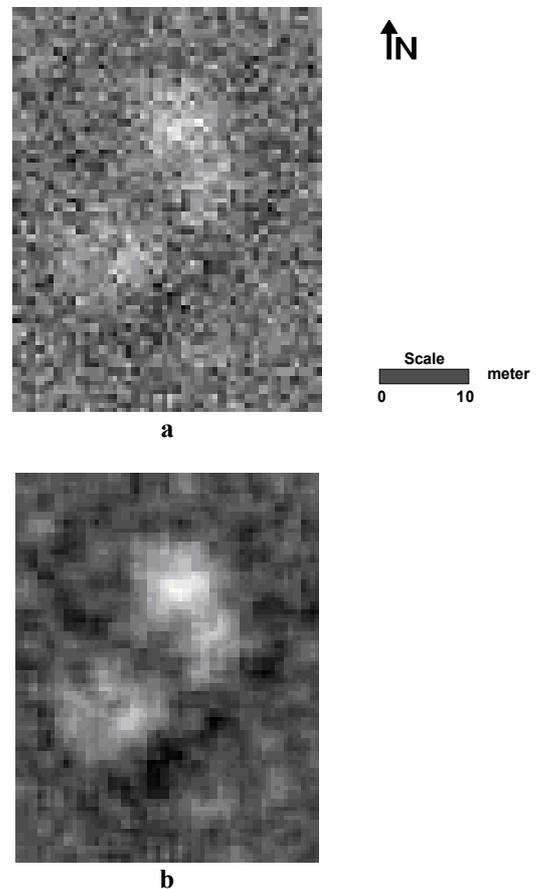
d

neighborhood level $m=2$ and quantization level $q=128$ (c) ICIPA output for third iteration, neighborhood level $m=2$ and quantization level $q=128$ (d) ICIPA output for fifth iteration, neighborhood level $m=2$ and quantization level $q=128$.

As a result, we can conclude that ICIPA is a very powerful algorithm in de-noising of synthetic examples.

3.2. Real Data

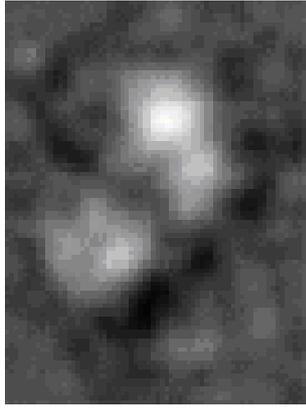
To further evaluate ICIPA algorithm, we have also worked with real data; we have especially chosen a very noisy data from a section of Sivas-Altınyayla Kusakli region of Hittite Empire ruins as shown in Figure 6.



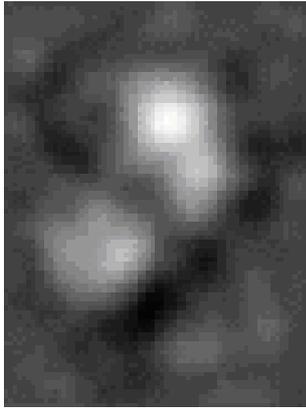
a

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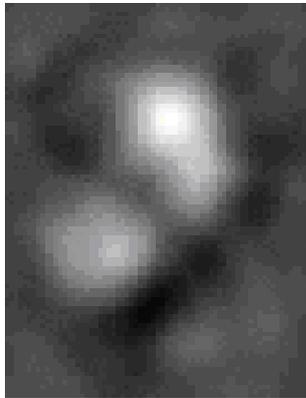
Figure 5. (a) 97% noise added form of the input data (b) ICIPA output for first iteration,



c



d



e

Figure 6. a Noisy real data b ICIPA output for first iteration, $q=128$ quantization levels, neighborhood level $m=1$, c ICIPA output for third iteration, $q=128$ quantization levels, neighborhood level $m=1$ d. ICIPA output for fifth, $q=128$ quantization levels, neighborhood level $m=1$ e. ICIPA output for eight iteration, $q=128$ quantization levels, neighborhood level $m=1$.

We expect that the noise effect on real data is about 87%. As shown in Figure 6b-e, the borders of Kusakli city are well found after a perfect de-noising process of ICIPA algorithm.

If we scrutinize the simulation results we can say that shapes which we are trying to reveal in noisy image appear better than previously when iterations are applied. In our proposed method, there are two more parameters, neighborhood coefficient m and color level q .

m is very important, because noise can be removed for some values of m but maybe cannot be removed for some other values. It depends on the percentage of the noise and the size of the shape that we are trying to find out. If the image has very high noise, the exact shape should not be more important than its location because maybe we cannot find the exact borders anymore. Thus the location can be found by using high values of m . In general we should use big templates to find the big shapes in high noisy situations and small templates to find small shapes. But we know that the worst case is that the shape is small and the noise is high.

The other parameter q can be chosen as two or more. We can choose q as 2 to determine the borders of the shape or more to distinguish the deepness of the shapes.

4. CONCLUSION

In this paper, we proposed “iterative cellular image processing algorithm” (ICIPA). The new unsupervised algorithm is an iterative algorithm which uses the advantage of stochastic properties and neighborhood relations of the input data. We have applied ICIPA algorithm to various synthetic examples and then a real data relating to the ruins of Hittite Empire. Satisfactory results are obtained for both synthetic and real data. Then we conclude that de-noising property of our scheme is the best in the literature.

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