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Developing a real-time pattern matching algorithm using artificial neural network for a reliable quality control in industrial applications

Endüstriyel uygulamalarda güvenilir bir kalite kontrolü için yapay sinir ağı kullanan gerçek zamanlı bir desen eşleştirme algoritmasının geliştirilmesi

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Abstract
Today, making quality control systems with reliable accuracy is very important in producing industrial products with zero defects. In this respect, it is an essential issue that camera control systems work with reliable control algorithms. In this study, a real-time control algorithm using a pattern matching algorithm has been developed to optimize the minimum contrast parameter with an Artificial Neural Network (ANN). In the study, the comparison of three algorithms included in pattern matching in terms of time was made using LabVIEW image control tools. Besides, one of the most critical parameters in the low-discrepancy sampling algorithm, which gives good results in time, minimum contrast parameter is discussed. The optimization of this parameter is done by using the Levenberg-Marquardt training algorithm in ANN. The obtained results show that the proposed pattern matching algorithm using ANN for optimizing the minimum contrast parameter is fast and effective for quality control applications.

Keywords: Artificial neural network, Pattern matching, Pyramid matching

Öz
Günümüzde kalite kontrol sistemlerinin güvenilir bir doğrulukta yapılması, endüstriyel ürünlerin sıfır hata ile üretimi hedefi açısından oldukça önemlidir. Bu açıdan, kameralı kontrol sistemlerinin güvenilir kontrol algoritmaları ile çalışması önemli bir konudur. Bu çalışmada, desen eşleştirme algoritmasını kullanan gerçek zamanlı bir kontrol algoritması, minimum kontrast parametresini yapay sinir ağı (YSA) ile optimize edecek şekilde geliştirilmiştir. Çalışmada örüntü eşleştirmeye dahil edilen üç algoritmanın zaman açısından karşılaştırılması LabVIEW görüntü kontrol araçları kullanılarak yapılmıştır. Ayrıca, zaman açısından iyi sonuçlar veren düşük-tutarsızlık örnekleme algoritmasında en önemli parametrelerden biri olan minimum kontrast parametresi tarışılmıştır. Bu parametrenin optimizasyonu YSA'da Levenberg-Marquardt eğitim algoritması kullanılarak yapılmıştır. Kullanılan yöntem sayesinde, desen eşleştirmesinin hızlı ve etkili olduğu görülmüştür.

***Anahtar kelimeler**: Yapay sinir ağı, Desen eşleştirme, Piramit eşleştirme*

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1. Introduction

Pattern matching technique is used in image processing in many areas such as tracking systems, quality control systems, counting processes, classification, and asset absence control. Pattern matching is the finding of the desired template image within an image. Thus, human errors in industrial applications have been minimized and made more stable. Many studies have been done in the literature on the subject (Kamtongdee et al., 2013; Hengdi et al., 2011; Panoiu et al., 2015; Hryniewicz et al., 2015; Patil and Ingle, 2020; Koniar et al., 2014; Rouget et al., 2018; Kalina and Golovanov, 2019; Zhou et al., 2020).

A study on the sex determination of silkworms (Kamtongdee et al., 2013) aimed to effectively classify weak silkworm pupae, an essential process in the silkworm industry. The normalized cross-correlation model is considered for silkworm gender identification. In another study (Hengdi et al., 2011), it was aimed to find defective characters in the bearing production process with the bearing character recognition system. Character recognition was done using normalization processes; character traits have been extracted and recognized. In another study on the subject (Panoiu et al., 2015), a study was conducted to recognize traffic lights. Character identification was made according to the color spectrum of traffic lights. LabVIEW National Instruments (NI) in a study of the application of image processing techniques using the Vision software (Hryniewicz et al., 2015), studies using the camera control technique for quality control of industrial products in the production process were made. In another study conducted in agriculture, weeds were determined to help the database's data to reduce the human factor (Patil and Ingle, 2020). The mechanical parts' visual control was carried out with different LabVIEW algorithms in ref. (Koniar et al., 2014). In the study, various field-programmable gate array (FPGA)-based pattern matching applications in industrial cybersecurity are discussed, and a few selected methods are compared (Rouget et al., 2018). In the study, an optical character recognition (OCR) algorithm based on template matching definition, which has adaptive binarization feature and does not require many training examples, is presented (Kalina and Golovanov, 2019). In the study, a systematic two-step model matching method is proposed to catch similar alarm floods in different processes (Zhou et al., 2020).

In this study, the development of the pattern matching algorithm was made by using LabVIEW image control tools. Quality control of an industrial part was performed in real time with the developed algorithm. The pattern matching technique using the normalized cross-correlation function as a mathematical model is considered for the quality control test of the marking on a machined piece of metal. Pyramid matching and low discrepancy sampling models were used as pattern matching techniques in National Instruments (NI) Vision. Pyramid matching accuracy percentages and low discrepancy sampling models for this metal piece tested were compared in terms of response time. One of the most critical parameters in the low-discrepancy sampling algorithm, which gives good results in time, minimum contrast parameter is discussed. This parameter's optimization is done using the Levenberg-Marquardt training algorithm in an artificial neural network (ANN). In the study, the mathematical model of the pattern matching technique is explained in Part II. Section III includes the simulation results, and the results obtained are given in Section IV.

2. Materials and methods

In this study, the pattern matching technique is discussed. Pattern matching is finding a template image in an image using the normalized cross-correlation function as a mathematical model (Gonzalez and Woods, 2008).

The correlation function is defined as $C\ (i,j)$;

$$C\ (i,j) = \sum_{x=0}^{l-1}\sum_{y=0}^{k-1} w(x,y)f(x+i,y+j) \quad (1)$$

where $w(x,y)$ template image in kxl size and $f(x+y)$ (where $k \leq m$ and $l \leq n; i = 0,1,\ldots,m-1, j = 0,1,\ldots,n-1$.) the original image in mxn size.

In NI Vision, the pattern matching method consists of two phases: training and matching. During the training phase, the algorithm extracts the gray value and/or gradient value from the template image, and this learned information is stored as part of the template image. This information stored in the matching phase is extracted from the examination image by the model matching algorithm. This algorithm detects matches by determining the area in the examination image, where the highest cross-correlation is detected (National Instruments, 2005).

NI Vision uses two models in pattern matching, namely pyramid matching and low discrepancy sampling.

2.1. Pyramid matching

The pyramid matching model is the spatial sampling of both the template and the target image at smaller resolutions using Gaussian pyramids (Jing et al., 2016). The image is first flattened with a Gaussian filter and then reduced to half size. This approach is done recursively and continues until the desired minimum size is reached. A matching approach is applied to Gaussian pyramids, starting with the lowest possible resolution, from less to more details (National Instruments, 2018). Pyramid matching model is shown in Figure 1 (Jing et al., 2016).

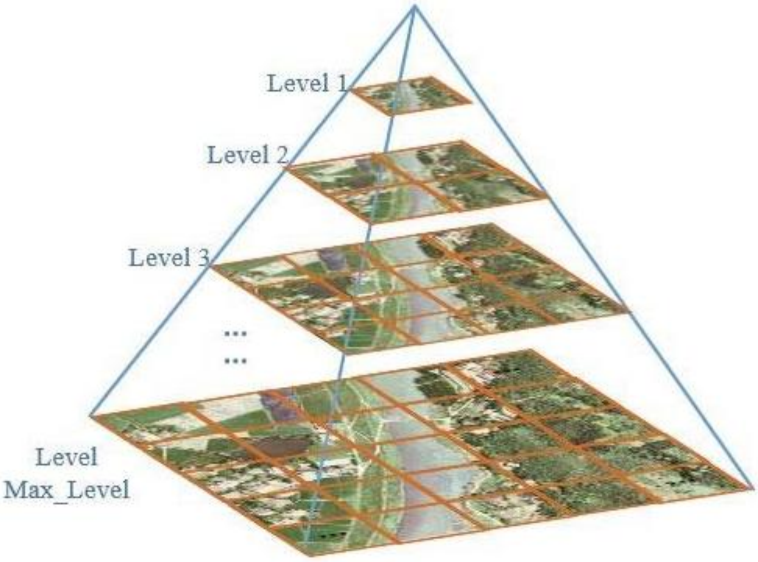

Figure 1. Visual representation of a 5-level image pyramid

In the study, the normalized cross-correlation is used for matching, and the square of the Euclidean distance between the two images is used as a measure of similarity.

Assuming that $w(x,y)$ template image in kxl size is placed in a $f(x+y)$ the original image in mxn size as in Figure 2, this dimension is defined as follows (Plötzeneder, 2010).

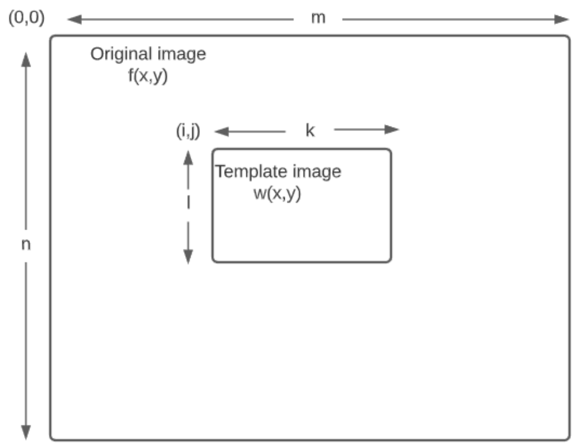

Figure 2. Correlation Procedure

$$d^2(i,j) = \sum_{x=0}^{l-1}\sum_{y=0}^{k-1}[w(x,y) - f(x+i,y+j)]^2 \tag{2}$$

$$d^2(i,j) = \sum_{x=0}^{l-1}\sum_{y=0}^{k-1} w(x,y)^2 - 2w(x,y)f(x+i,y+j) + f(x+i,y+j)^2 \tag{3}$$

In equation (3), the total energy of the template image;

$$\sum_{x=0}^{l-1}\sum_{y=0}^{k-1} w(x,y)^2 \tag{4}$$

is constant. Assuming that the density in the target image is more or less evenly distributed;

$$\sum_{x=0}^{l-1}\sum_{y=0}^{k-1} f(x+i,y+j)^2 \tag{5}$$

Approximately constant. As a result, equation (2) remains the cross-correlation equation.

$$C\,(i,j) = \sum_{x=0}^{l-1}\sum_{y=0}^{k-1} w(x,y)f(x+i,y+j) \tag{6}$$

Here, if the original and template images coincide in (i,j), it is concluded that these images are similar. However, the matching fails in case of a change of image energy position. In such cases, a normalized correlation term is calculated. where t(i,j) is the average density in the template and the average density of the target image in the region overlapping the template (Plötzeneder, 2010),

$$t(i,j) = \frac{\sum_{x=0}^{l-1}\sum_{y=0}^{k-1}(w(x,y)-\overline{w})(f(x+i,y+j)-\overline{f(i,j)})}{\sqrt{\sum_{x=0}^{l-1}\sum_{y=0}^{k-1}(w(x,y)-\overline{w})^2\sum_{x=0}^{l-1}\sum_{y=0}^{k-1}(f(x+i,y+j)-\overline{f(i,j)})^2}} \tag{7}$$

is the normalized correlation function.

In NI Vision, the pyramid matching model is divided into a gray value method and a gradient method. While normalized pixel values are used in the gray value method, filtered edge pixels are used in the gradient method. Also, in the gradient method, vector correlation is used instead of normalized cross-correlation. The gradient method is also faster than the gray method, as less data is stored. However, it provides a very low solubility in the edge of the gradient method's sturdiness, and reliability is reduced in a higher resolution than the gray value model.

2.2. Sampling of low discrepancy (Image understanding)

Methods based on low discrepancy sampling are based on selecting pseudo-random points according to how accurately they represent their neighborhood. The template image is generally sampled with low discrepancy sequences such as Halton, Sobol, or Faure. In NI Vision, as seen in Figure 3, a smart sampling technique that includes edge pixels and region pixels is used to reduce the image's excess information (National Instruments, 2018).

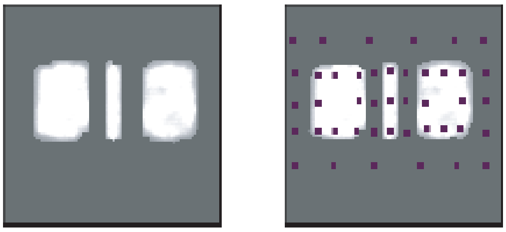

Figure 3. NI Vision low discrepancy sampling

In this sampling method, after the points are classified to the neighborhood value to increase efficiency, minimal values are discarded. Then, points with very high value are selected and used for cross-correlation search in the target image.

However, in this sampling, templates containing similar grayscale large regions and minimal templates may cause image analysis problems due to the small number of sample points (National Instruments, 2018).

3. Experimental study

The NI Vision Development Module (VDM) library is used for the system, and in Figure 4 below. The Pattern Matching Sub Virtual Instrument (SubVI) of the algorithm is below.

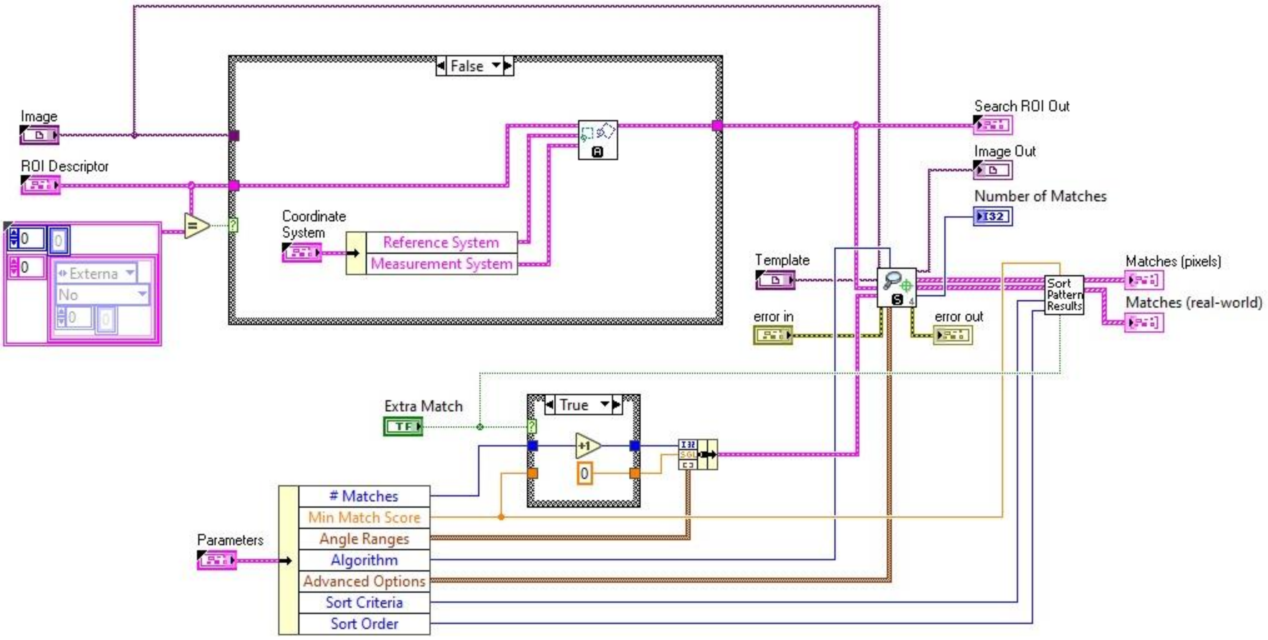

Figure 4. Match Pattern – Algorithm SubVI

The program working principle has two main stages. First, the image is taken, converted to Hue Saturation Lightness (HSL) form (Grayscale). The desired results are then obtained with the input parameters in the Image Acquisition (IMAQ) Match Pattern 4 library block in Figure 5 in the NI VDM.

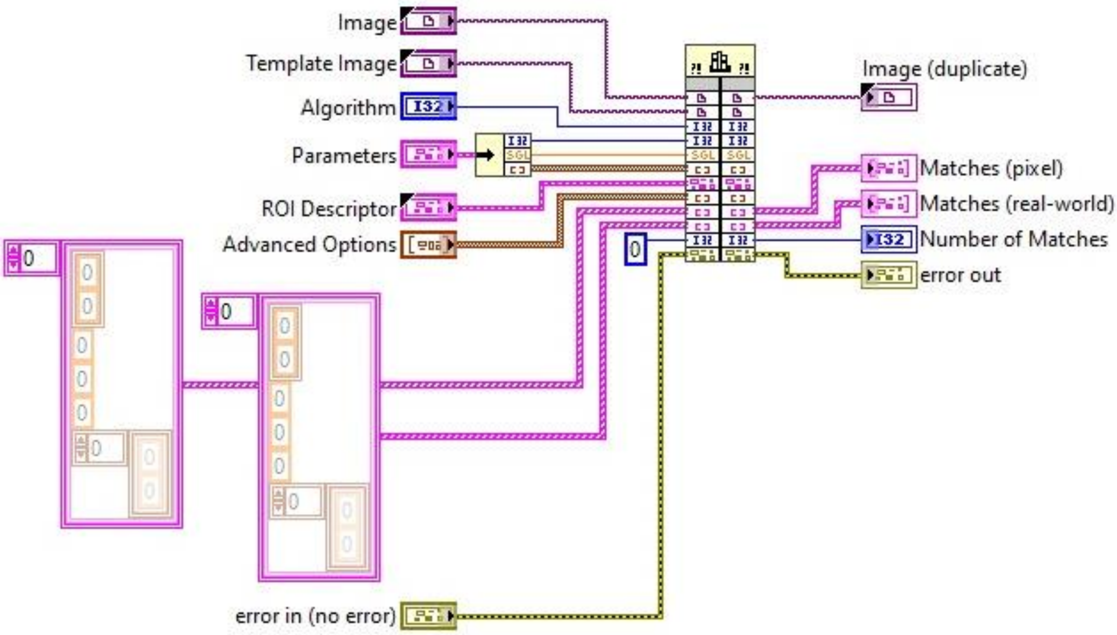

Figure 5. NI_Vision_Development_Module: IMAQ Match Pattern 4 Library Block

A high resolution adjustable focal point USB-connected camera and a ring-shaped LED lighting with adjustable light intensity are used in the system. Since the illumination and light intensity of the environment can change, it has been simulated with many photographs taken from a fixed angle in the dark environment. The working environment, camera, lens and lighting in the test system are shown in Figure 6. The values used for Camera and LED lighting are given in Table 1. The metal piece is also set at a distance of 30 cm from the camera and at a 90-degree position.

Figure 6. Experimental work environment and test system components

Table 1. Camera and LED lighting values

Camera	
Model	ELP-USB4KHDR01
Sensor	SONY IMX 317 (1/2.5")
Resolution	3840 x 2160 p
Power Supply	5V DC 200 mA
Lens	5-50 mm manual varifocal
LED lighting	
Inner Radius	60 mm
Outer Radius	95 mm
LED Type	F3
LED Quantity	144
Brightness	Adjustable

In NI Vision for pattern matching technique, numerical values are used in Table 2 for the low discrepancy Sampling model and in Table 3 for the pyramid matching model.

Table 2. Low discrepancy sampling parameter values

Matching Parameters	
Minimum Contrast	10
Search Strategy	Balanced
Initial Match List Length	300
Match List Reduction Factor	3
Initial Step Size	5
Intermediate Angular Accuracy	2
Subpixel Parameters	
Enable Subpixel Accuracy	True
Subpixel Iterations	20
Subpixel Tolerance	0

Table 3. Pyramid parameter values

Matching Parameters	
Maximum Pyramid Value	3
Minimum Contrast	10
Initial Match List Length	300
Match List Reduction Factor	0
Intermediate Angular Accuracy	6
Process Border Matches	True
Overlap Parameters	
Minimum Match Separation Distance	20
Minimum Match Separation Angle	10
Maximum Match Overlap	20
Subpixel Parameters	
Enable Subpixel Accuracy	True
Subpixel Iterations	20
Subpixel Tolerance	0

Figure 7-a gives the image of a machined metal part. The branded logo template image in Figure 7-b was searched for in this image. The logo image was manually trained in NI LabVIEW Vision, and the template image was obtained.

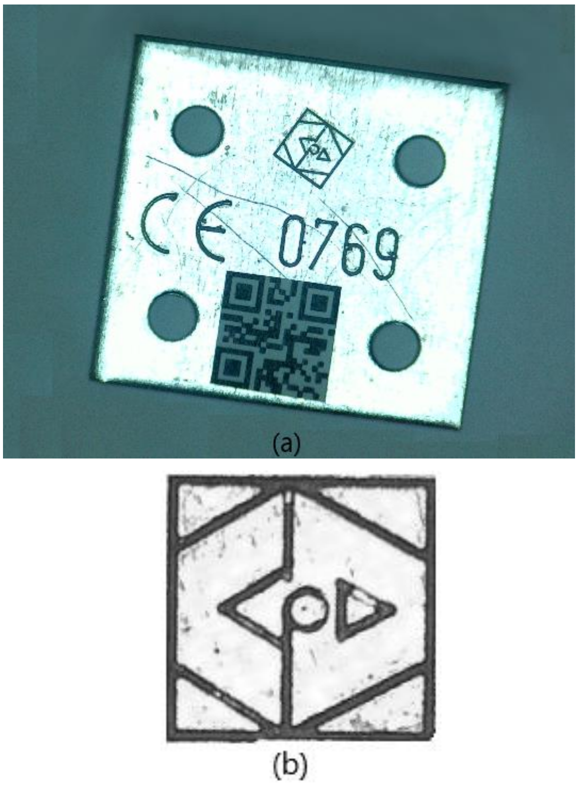

Figure 7. Machined metal part (a) original image (b) template image

4. Results and discussion

Finding the template image was made using the gray and gradient methods in the low discrepancy sampling and pyramid matching model. These matching models were compared over 100 different machined metal part images in terms of time and accuracy percentage, and the average time value was calculated. Finding the template image in the rotated original image in all three models is shown in Figure 8.

Figure 8. Capturing the template image

The average response time in the results obtained; was 98.6 ms for low discrepancy sampling, 785.6 ms for the gray value method, and 335.6 ms for the gradient method. Thus, low discrepancy sampling gave better results than pyramid matching. When the methods in pyramid matching were compared, it was observed that the gradient method gave a better result compared to the gray value method. The pattern matching algorithm using the normalized cross-correlation function as a mathematical model is discussed in this study. A machined piece of metal is used for pattern matching applications. Finding the logo image in the image of a machined metal part was compared with the pattern matching models in NI Vision in terms of time, and the performance values are given in Table 4.

Table 4. Pattern matching performance values

	Iterations	Total Time	Average	Std-Dev	Shortest	Longest
Low discrepancy sampling	100	9860.112 ms	98.601 ms	4.069 ms	91.944 ms	114.498 ms
Gray value method	100	78558.551ms	785.586 ms	13.490 ms	761.826 ms	809.278 ms
Gradient method	100	33558.950 ms	335.589 ms	6.174 ms	326.115 ms	372.395 ms

The low discrepancy sampling algorithm uses different NI LabVIEW parameters, and other parameters are also affected depending on the selection of these parameters. In this method, by using the parameter values within the ranges with a performance ratio of 100%, the effect of the value changes of the "minimum contrast" parameter on the average time has been investigated. By changing the "minimum contrast" and "initial step size" parameters, the average time spent in that process was calculated in the tests performed with a large number of values, and these values were inserted into the Artificial Neural Network (ANN).

While there is "initial step size" and "minimum contrast" in our network's input layer, there is an average value of the processing time at the output. There are 20 neurons in the network structure's hidden layer and one neuron in the output layer. As the activation function, the sigmoid function is used in the hidden and softmax function in the output layer. Levenberg-Marquardt was used as the training algorithm. Seventy percent of the data were used for training, 15 percent for verification, and 15 percent for testing (Table 5).

Table 5. Proposed method R and MSE values

	Percent	MSE	R
Training	70%	0,26197	0,999611
Validation	15%	7,67938	0,996131
Testing	15%	1,52860	0,988176

The Levenberg-Marquardt algorithm is designed to approach quadratic training speed without having to calculate the Hessian matrix. When the performance function has the form of a sum of squares, the Hessian matrix can be predicted and the gradient can be defined as (Parmar et al., 2017):

$$H = J_k^T J_k \tag{8}$$

$$g = J_k^T e \tag{9}$$

Here, J_k^T , is the Jacobian matrix for kth input containing first order derivatives of network errors according to weights and biases, and e , is a vector of network errors. The Jacobian matrix can be calculated using a standard backpropagation technique, which is much less complicated than computing the Hessian matrix (Parmar et al., 2017):

$$W_{k+1} = W_k - [J_k^T J_k + \mu I]^{-1} J_k^T e_k \tag{10}$$

Here, I is the identity matrix, W_k is the current weight, W_{k+1} is the next weight, e_k the additional final total error and μ is the combination coefficient.

The average processing time was found by ANN taking advantage of two critical parameters. Also, the optimal minimum contrast parameter value has been obtained by taking the smallest of these values. It is seen in Figure 9.

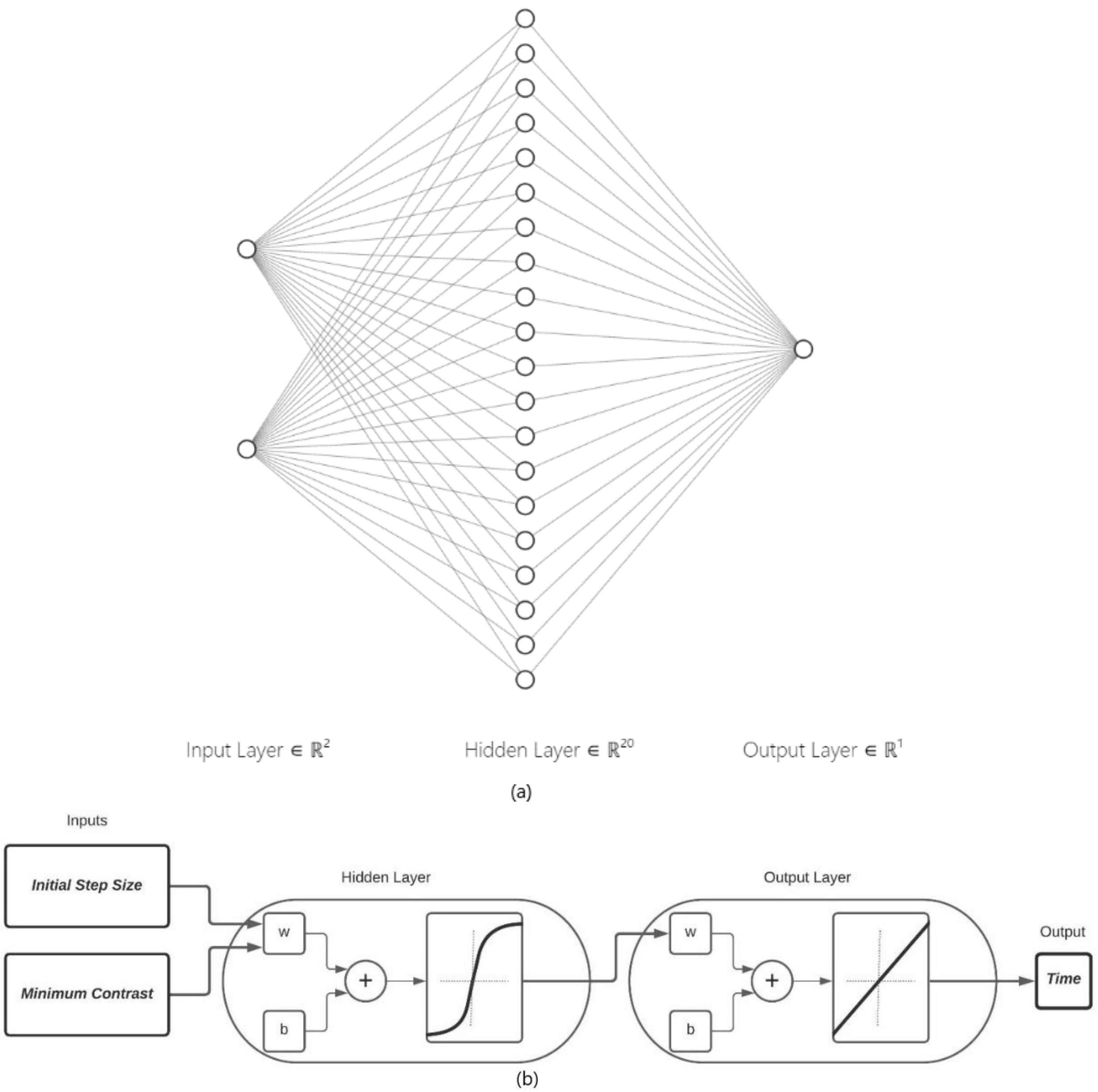

Figure 9. The optimal minimum contrast parameter value determined by ANN (a) ANN structure (b) ANN flow diagram

Mean Square Error (MSE) was found as a performance criterion, and R-value for correlation was found. It is seen in Figure 10. The results show that the proposed ANN-based optimal parameter tuning algorithm provides 99,776% accuracy with a pattern-matching algorithm.

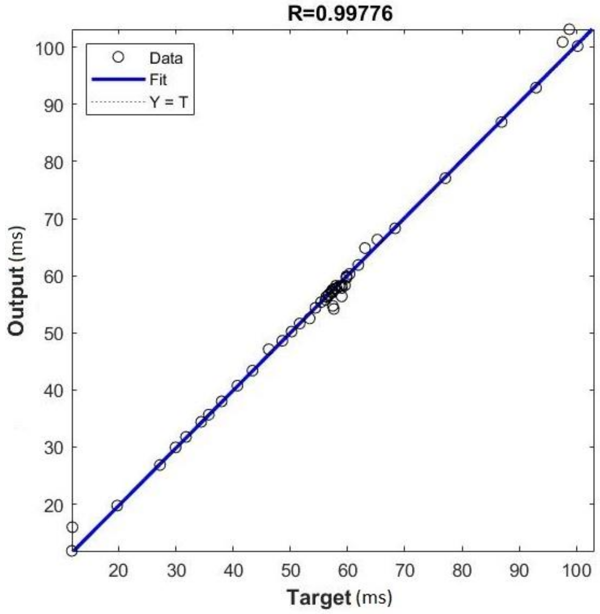

Figure 10. Correlation graphic

5. Conclusion

In this study, the comparison of three algorithms included in pattern matching in terms of time was made using LabVIEW image control tools. The results showed that the low discrepancy algorithm provided better performance than pyramid matching. Simultaneously, the gradient value method in Pyramid Matching gives better results than the gray value method. Although these methods differ in time, they are similar in finding the template image as a percentage. In addition, one of the most critical parameters in the low discrepancy sampling algorithm that gives good results in terms of time, the "minimum contrast" parameter is discussed. The optimization of this parameter is done by using the Levenberg-Marquardt training algorithm in ANN. Through the method used, pattern matching is fast and effective. Thus, unlike the simulations, a real-time system was designed in this study using both hardware and software. It was also seen that the proposed method gives more stable results for real-time applications by determining the most effective parameters of low discrepancy sampling with ANN.

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