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IMAGE ENHANCEMENT IN INDUSTRIAL WELDING ENVIRONMENT WITH IMAGE PROCESSING TECHNIQUES

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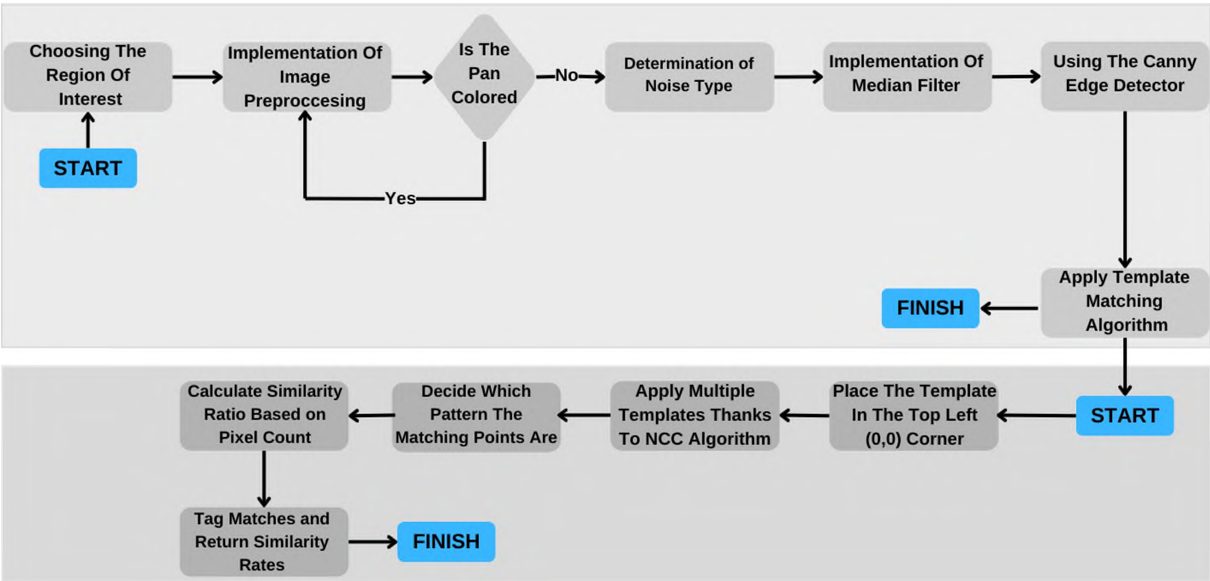
Highlights

- The importance of filtering and preprocessing stages in images
- Using template matching algorithm
- Applying NCC Template Matching Algorithm to Images
- Industrial Welding Processes

Graphical Abstract



Template Matching Algorithm in Welding Robots

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ABSTRACT: With the increase and acceleration of production capacity, computer-based control mechanisms are becoming increasingly common in industrial applications. The use of intelligent welding robots in the welding industry is increasing due to their instant decision-making and application capabilities. For this reason, computer vision systems and image processing algorithms are increasingly used. Although visual limitations in sensors and industrial environmental conditions (arc, noise, dust, etc.) cause problems in robotic welding applications, computer-controlled systems achieve much more efficient results than operator-controlled systems.

One of the most important points here is the applicability and stability of the algorithm to the system. In this study, considering the computational load of image processing algorithms and the negative effects of this computational load in moving environments, a more stable and efficient image feature extraction algorithm was tried to be created for robotic welding applications. After the welding process, object recognition was performed by performing object feature matching with the help of samples taken from the weld images. A new algorithm was created to recognize welding processes that differ from each other in some aspects with multiple samples and even to detect different types of welds. This algorithm reduces the images to gray level and performs a pre-processing step to remove noise with a filtering process, then detects the weld points with the help of predetermined templates and decides how accurately these points are made. Thanks to the NCC Template Matching method used in the algorithm, the running time of the algorithm is accelerated and more accurate results are obtained by introducing more than one template

Experimental method aimed both to calculate the accuracy rate in case the same type of weld operations are different from each other and to recognize the operations performed with different types of welds. While the detection level was around 60% in images without image preprocessing, the detection rate exceeded 70% in images with image preprocessing. In the experiments conducted on the images taken with the Template Matching algorithm, it was observed that the detection rate increased to around 75% at different threshold values. In addition, with the region of interest selection and NCC method, the running time of the algorithm was reduced to 190 ms on average.

Considering the results obtained in the experiments, the algorithm significantly improved the accuracy rates of spot welding and the differentiation of different weld types. By using sufficient light welds and correct experimental equipment, the success rate of the Template Matching algorithm has been increased and the processing load has been alleviated. The effect of external environmental conditions, which is considered the biggest disadvantage of the algorithm, is minimized with lighting elements.

Keywords: *Object Recognition Based Template Matching, Image Filters, Full Frame Method, Pattern Matching Method, Industrial Welding Process*

1. INTRODUCTION

With the rapid development of the modern manufacturing industry, more and more welding robots are being applied in automated production processes. Welding robots are used in many fields thanks to their high productivity, consistency of quality and uninterrupted operation even under adverse working

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conditions [1]. Welding robots, which are widely preferred in areas such as the automotive industry and shipbuilding processes, play an important role in compensating for operator-induced errors. They can also provide more autonomous and flexible working conditions. They are supported by computer-based applications to provide this flexibility and autonomous operation. Today, operators are replaced by computerized vision systems. In order to integrate these vision systems, some results must first be obtained and these results must be transferred to the hardware. For this reason, most welding robots are teach-and-operate robots. Parameters can be taught to the computer using previously obtained test results and the weld can be evaluated as a result of this learning. But during the welding process, radiation, heat propagation paths, gap variations, stepped edges, etc. often cause distortion of the seam position [1]. If this seam position change is not corrected, it reduces the weld forming quality. These factors negatively affect robots that are programmed as teach-and-play. Therefore, to solve this problem, the use of image sensors and dynamic programming with instantaneous feedback is proposed. The purpose of this feedbacks are to imitate the movements of the human welder in order to develop smart robot welding. Three basic technical steps are required to perform automatic welding by imitating a human welder. The first is to acquire and perceive information about the dynamic welding process, such as how it is acquired by human sensory organs, to detect internal and external welding conditions. The second is to extract the characteristics of the welding assembly, i.e. model the dynamic welding process; the third is to develop a human brain-like controller to manage the process to determine control methods. Seam tracking is a major problem in intelligent robotic welding, and visual sensing technology is an effective way to deal with it. With the help of image-based seam tracking technology, traditional teach-and-play robots can overcome challenging conditions during welding application and fulfill high-quality welding requirements [2]. These detection processes are provided by cameras and software. At this point, the images from the cameras need to be processed quickly and accurately. In order for images to be processed quickly, image quality and resolution must be good. Here, vision sensors are supported in a variety of ways to ensure good visibility. These supports can be lighting elements, laser strips, etc. Vision perception technology can be divided into passive vision and active vision. Passive vision uses the arc as a light weld, and its images contain rich information. Active vision is the method that uses an external light weld. One of the most popular non-optical detection methods is arc detection [3-5]. The difference between passive and active methods is based on the use of an optional light weld. Active vision uses a camera device and a light weld while passive vision uses two camera devices that are not light welds. In passive vision, due to the complex nature of the weld environments, a wide variety of methods have been proposed by the researchers. Two different types of information can be obtained using a passive vision system; alternatively, the seam profile (1) obtained using active vision and the weld pool profile (2) obtained by passive vision only.

Unlike active vision, which provides only one point at a time, passive vision systems can be used holistically to achieve the stitch path. Numerous techniques have been proposed for image pretreatment, seam profiling and weld pool profiling of the passive vision system. In the active vision system, triangulation is applied to find the geometric features of the seam. The detected points are accepted as peaks in certain regions and triangular shaped areas are found and coordinates are calculated according to this triangle. It uses a camera and light weld device to capture the image of the weld seam.

There are several methods commonly used for positioning in the second and third stages of welding robots. Some of these methods include teaching and playing, visual perception, offline programming, and coordinates. The method of teach-operate is used only for teaching and positioning, but the efficiency and autonomous control of this method are low. In such systems, visual detection methods can be used to detect weld seam for teaching [4]. However, most welding robots are teaching and operating robots. Parameters can be taught to the computer using the test results obtained earlier and the weld to be made as a result of this learning can be evaluated. Offline programming requires a lot of preparatory work, and the location of the robot and its welding parts in the virtual environment should be the same as in the real environment. There may be some discrepancies between preliminary studies on these parameters and in practice. A serious preparation process is necessary to resolve such situations.

With the increase and acceleration of production capacity, computer-based control mechanisms are becoming increasingly common in industrial applications in order to prevent loss of time in this preliminary preparation process. In the welding industry, the use of intelligent welding robots is becoming widespread due to instant decision making and application. For this reason, computer vision systems and image processing algorithms are increasingly being used. Visual limitations in sensors and industrial environment conditions (arc, noise, dust, etc.) cause negativity in robotic welding applications. Despite these disadvantages, computer-controlled systems achieve much more efficient results than operator-controlled systems.

Based on these disadvantages, it has been shown that each method of various template matching algorithms has its own different application areas, advantages and disadvantages. The NCC method is used in high-speed industrial applications and is a very suitable method for finding multiple patterns simultaneously. However, this method may fail due to brightness changes and object displacement. On the other hand, it is a very effective method for searching and finding templates through took images. Another disadvantage about this algorithm is that it is slow. That is why we used NCC Template Matching. But NCC have some problem about industrial environment. It is proposed to solve the problem of NCC being affected very quickly and badly by brightness and complex background by trying different methods. Although this method is widely used in object tracking and outdoor applications, it requires optimization to precisely determine pixel coordinates [6, 7]. The results obtained here show that the NCC algorithm can also be used in this study. In this study, the NCC template matching method was chosen because it can scan more than one template at the same time.

Thanks to this experimental study that we made, the low performance of the Template Matching algorithm, which is easily affected by such conditions, has been improved in harsh industrial environments. Thus, the disadvantages of computer-controlled systems are tried to be eliminated. This is achieved by identifying multiple templates, making different pairings at the same time, and using the right lighting patterns.

After the region of interest of the strip was obtained, segmentation and edge detection algorithms were used. After detecting the edges of the weld strip, a detection algorithm based on the intensity distribution of pixels and neighborhood search is proposed. Another method used to find the edge features of the pool is histogram values. The histogram gives us edge information based on pixel density. During the application, difficulties were encountered such as rotation of the laser strip and too much reflection of the laser. The algorithm failed in the case of rotation, but gave positive results against laser reflection. Additionally, the average image processing time for 1200x1600 resolution images is 300 ms. Welding operations are carried out at an average speed of 0.1 m/sec. For welding, which is generally a very slow process, processing three images in one second is practically sufficient [8]. IN this experimental study, the processes defined on average around 250-320 ms have been reduced to 180-200 ms thanks to image preprocessing and NCC Template Matching method applications. In this way, welding robots, which are usually programmed offline in teach-play format, can be used with instant feedback. Considering other studies in the literature, this study tried to provide a more optimum light weld and lighting conditions since the template matching algorithm is affected by light and background parameters. In addition, healthier templates were selected for the NCC method, thus affecting the speed and robustness of the algorithm less. The algorithm applied to the weld points gave good results despite the high threshold rates against light reflection. Although high threshold values were determined in the preprocessed images, it managed to detect three of the four points.

In another study, CCD image sensor, line laser and optical lenses were used to monitor the weld seam. The optical system of the sensor enables reasonable selection of laser sensor light weld and filter band for arc characteristics; this solves the problem that the laser power of the sensor differs greatly from the arc intensity in the arc welding. It enables the image detection system to obtain an ideal laser stripe image. The purpose of calibration for the imaging system is to find the transformation relationship between the pixel coordinates of the image and the three-dimensional coordinates of the objective world. The mathematical description of the parameters of this transformation relationship is determined by the imaging model of the visual system. After this model is determined, line correction operations are applied with image processing models. In this study, stitch tracking was performed using fast image segmentation and convolutional neural networks. However, since there is a lot of arc flash and spatter, the sensor calibration, robot processing module and seam tracking system need to be developed [9].

The experimental set used in this experiment was avoided from being complex. In addition, external light welds were used to directly process camera images without the need for different visual perception devices. In this way, the experimental set was simplified and extra expenses were avoided.

As a result, with this experimental study;

- The usability of the Template Matching technique in the industrial environment has been increased.
- By increasing the algorithm speed, instant workability with welding robots has been ensured.
- The processability of the images was ensured with noise and filtering steps.
- It has been shown that weld detection of colored pans can be done with edge detection algorithms.
- It has been shown that both the same type of welds can be classified and different types of welds can be detected with a single algorithm.

2. METHODOLGY

There are many types of welding seams in real industrial production. The seam lift method based on morphological image processing is always designed for a specific weld seam. To perform different types of welding processes, the property extraction algorithm must be evaluated according to the shape characteristics of different welding seams. Therefore, the flexibility of the algorithm is relatively poor. Meanwhile, when many images are faced with the morphological processing step, the real-time performance of the stitch tracking will be affected [1].

The type of seam in the images used in this study distinguishes the template matching algorithm from other image processing algorithms. Because the similarity of the weld points can be easily detected by the template matching algorithm. The template should contain the features in the images. The similarity of such weld played an important role in determining the algorithm selection as Template Matching. In the experimental setup, a KUKA brand robot arm was used as the welding robot, as seen in Figure 1. This robot used in the experimental study uses a KR C5 processor. It consists of 6 axes. These axes are controlled by angular positioning. This robot performs welding operations at an average speed of 0.1 m/s. It has a load carrying capacity of 10 kg. It has an average accessibility range of 1500 mm. This welding robot is used to weld aluminum-nickel alloy pans used in the food industry for cake production. Welding is the process of welding the pan-shaped material into which the cake dough will enter the mold. These molds are made by attaching them to the pan from its four corners. These welding operations must be welded by properly centering in order to produce correct cakes. Therefore, an experimental study was carried out to determine whether the welding points were made correctly.

The images used in the study were processed using the OpenCV V4.5.3 library in the Python 3.9 version environment with the Template Matching algorithm.

Figure 2 shows what the welded pans look like. As mentioned before, the molds welded to the pan from its four corners are welded by centering them. Since some of the weld points are displaced, these faulty pans can become unusable. For this reason, in order to prevent this situation, the images taken with the camera are processed with image processing and the aim is to minimize errors.

Figure 1. Robot Used In The Welding Process

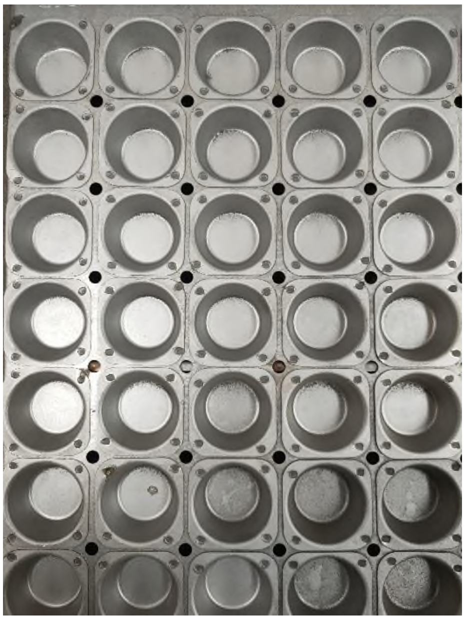

Figure 2. Image of Welded Cake Pan

The images were subjected to morphological processing. These operations are performed matrically. When applying the necessary signal processing methods to images, the image is treated as a two-dimensional matrix. A digital image with M rows and N columns is displayed in the form of f(x,y). This is because the values in their coordinates (x,y) become discrete values. This makes it easy to specify image pixels. Thus, the values at the origin (x,y) of the coordinates are represented as = (0,0). In Equation 1, an image with rows M and columns N is represented in coordinates. f(x,y) represents a pixel for each element; and so on; and so on; and so on; and so on; and so on; and so on; and so on; an image with M rows and N columns has MxN pixels. Expressing rows and columns in this way makes it easier to apply algorithms to the image and express how they are applied. Thus, the positions of the detected weld points are more easily expressed. The distance to the reference point of the weld to the robot can be provided as feedback.

$$f(x,y) = \begin{bmatrix} f(0,0), & f(0,1), \ldots\ldots f(0,N-1) \\ f(1,0), & f(1,1), \ldots\ldots f(1,N-1) \\ . & . \quad . \quad . \\ . & . \quad . \quad . \\ . & . \quad . \quad . \\ . & . \quad . \quad . \\ f(M-1,0), & f(M-1,1), \ldots\ldots f(M-1,N-1) \end{bmatrix} \tag{1}$$

The steps of our work are given below, step by step.

a. Image Development

Basically, the aim is to make some improvements to the image, better detect the features of interest, and thus create a better input to the image processing algorithm to be implemented [9]. The main purpose of image enhancement is to create an image that is more suitable for the observer by highlighting the characteristics of the image.

Figure 3. a) Original Image b) Enhanced Image

Figure 3 shows an image enhanced by the image enhancement method. Here, better input images were obtained using various filtering tools. Because the type of noise in the image was salt and pepper noise, the type of filter was chosen as a median filter.

b. Object Recognation

The process of finding the object to look for in a picture. For any object in an image, there are multiple points that can be removed from the object to identify its properties. These points, which are extracted from the object and provide rich information about the object, are used in images where the object to be detected is in the same frame as more than one object, they help to recognize and detect the object [10]. Algorithms such as template mapping can also perform object recognition by comparing pixels sequentially.

Figure 4. a) Original Image b) Recognized Object Image

Figure 4 shows the input image of the algorithm and the image of the detected object. Templates set as examples for the detection of weld points are defined. As all the weld points are similar to each other, detection is not difficult thanks to the taught template. However, since the coordinates of the weld points are different, it can interfere with the detection process. This intervention can be done with threshold determination or image preprocessing. In this case, both the noise in the template image and the weld image must be removed. It is aimed to detect the weld made on different colored patterns pre-treated with Canny edge detection algorithm by applying the template matching algorithm.

Again, to more easily detect the weld points scattered across various regions of the image, the ROI region is selected from the image and the part where the weld point is to be detected is narrowed. Thus, the parts where other welding points are located can be more easily detected by ignoring. In this study, thanks to the ROI, instead of focusing on the whole cake pan, each of the cake molds is individually focused, reducing both the algorithm time and the processor's processing load. In different applications, ROI has been used for different purposes. For example, in the spot welding seam, the continuous welding seam detection is made as follows:

1) ROI Selection: Before removing the property, it is necessary to select two ROI zones, including laser strips and welding seams, respectively. If the image selected as a template contains only the weld type, it can be very useful in selecting ROI. Thus, only the welded region in the image can focus faster. As we can see in equation 2:

$$\begin{cases} x = \frac{x_0}{4} \\ y = y_0 + \frac{h}{2} + w \\ w = x_0 + 2 \\ H = 2 * w \end{cases} \tag{2}$$

(x, y) welding seam is the image coordinates of the upper left corner, (x0, y0) is the image coordinates of the upper left corner of the ROI of the laser strip, (w, h) is the width and height of the area of the weld seam, the, h and w are the ROI height and width of the weld.

2) In the removal of the welding seam edges, the average gray value of the image is calculated before the edge is removed. The gray level values of the pixels are then compared to a threshold value set by the user or using a function called Otsu. If the gray value of the pixels is smaller than the threshold, logarithmic conversion and normalization are used to improve the original image.

3) In the determination of edge fitting equations, the gradients of the points on the two sides are opposite. They can therefore be easily distinguished. Using the Canny edge detection algorithm, the edges are identified by detecting high frequency transitions in the image. Since the gradients of these transitions are opposite to each other, it is concluded that the regions involved contain edges. Points that meet the

edge criteria can be maintained as absolute edge points. Similarly, hysteresis thresholds are used to filter false edge points [2].

Figure 5. a) Welded Cake Pan b) ROI Area

Figure 5 shows the region selection where the points of weld are identified using ROI. The pixels of these images are reduced to gray level. This step was applied to perform thresholding on the images.

2.1. Image Preprocessing

There are several methods used to remove noise from the resulting images and keep the data of interest intact. In this way, it is ensured that the algorithm to be used gives healthy results. By applying various filter operations to the noisy image, the noise is eliminated so that the algorithm can provide more accurate results. In the filtering step, unnecessary details are removed by removing salt and pepper noise in the image. These filters also improved the data quality by making contrast changes more pronounced and sharpening the edge information in the image.

There are various types of noise as different factors cause noise generation. A good image filtering algorithm is expected to give good results when applied to different types of noise. Noisy image is defined as in Equation 3:

$$f(i,j) = g(i,j) + n(i,j) \tag{3}$$

Where f(i, j) is the intensity value of the image, n(i, j) is the gray level value of the noise and g(i, j) is the intensity value of the pixel without noise. There are many filter methods to reduce noise in images. One of them, spatial plane image filters, is divided into linear and nonlinear. In general, in the nonlinear method, the filtered image is determined by the intensity values of the pixels in the filter mask with the help of ordinal statistical methods. In linear methods, filtering is done by applying the filter mask to all pixels individually.

A filter type was chosen according to the type of noise detected in the weld images. The purpose of using the median filter is to remove unwanted data and emphasize the data of interest. The median filter can also retain detailed information such as edge segments and sharp seam angles. In median filtering, the input intensity is replaced by the median of the intensities present in its neighboring pixels. The size of the filter used depends on the welding application and the configuration of the welding system [12]. For salt and pepper noise, the use of a linear filter such as a mean or Gaussian filter reduces the effect of the noise on the processed pixel but distorts the information in the noise-free pixels. For this reason, linear filters are not preferred and nonlinear filters are used to remove salt and pepper noise. Because outliers can be easily removed in non-linear filters. The minimum filter, which assigns the smallest intensity value of the pixels in the region within the filter window to the processed pixel, gives good results for images containing salt noise. The maximum filter, which assigns the highest intensity value from the intensity values in the filter mask to the processed pixel, gives good results in removing pepper noise. However, the maximum filter does not work well with salt noise and the minimum filter does not work well with pepper noise. Since salt and pepper noise were detected in the images used in this study, median filtering, one of the nonlinear method filters, was proposed. Median filter is one of the most commonly used nonlinear filters to reduce salt and pepper noise. The median filter is expressed using the equation 4:

$$y(i, j) = median\{x(m,n),(m,n) \in w\} \tag{4}$$

Where w refers to the neighboring pixels depending on the kernel size, and this size can be varied according to the application. Since the intensity values of the pixels in the neighborhood of the processed pixel in the median filter are ordered from small to large and the median value is the intensity value of the processed pixel, values close to the maximum and minimum values are successfully eliminated. Intensity values with extreme values are eliminated because values close to the maximum and minimum, i.e. noisy pixels, will be found at the beginning or end of the row and the mean value will form the filtering result. Therefore, the median filter is highly effective in removing salt and pepper noise or impulse noise. Another benefit of the median filter is that it preserves the details in the image by reducing the distortion caused by filtering [11].

Figure 6. Image Reduced to Gray Level

Figure 7. Image filtered using the median filter

Noise is removed by superimposing it on the kernel image. K is the kernel matrix used for filtering in NxN dimensions, I_R is the matrix of the color image from the camera, and I_R^I is the new image matrix at the end of filtering. Equation 5 provides the formula for calculating the new values for each pixel.

$$temp = \frac{N}{2}$$
$$I_R^I(x,y) = \frac{1}{NxN}\sum_{i=1}^{N}\sum_{j=1}^{N} K(i,j) * I_R(x+i-temp, y+i-temp) \quad (5)$$

It is desirable to use negative values in the I_R matrix during the filtering process. In this case, the value in the index closest to the relevant indexes is used. For example, $I_R^I(0, 0)$ multiplied by the closest value in the K(0, 0) matrix for $I_R(-1, -1)$, $I_R(0, 0)$ was used in the calculation. Since the image has three channels and was captured in RGB (Red, Green, Blue) color space, the values of the three colors in the I_R image matrix are updated using equation 5. After the image is reduced to gray level, the filtering step comes next. For example, when calculating K(0,0)* $I_R(-1, -1)$ for $I_R^I(0, 0)$, the closest value in the matrix I_R (0, 0) is used.

The median filter provided a simpler image after the image was reduced to gray level. This makes it easier to extract edge points with the Canny edge detection algorithm. As a result of these preprocessing processes, it is aimed to obtain similarities between the template and the image more easily, to shorten CPU operations and to prevent the similarity ratio from decreasing due to unnecessary data. The results of the applied median filter are shown in Figure 6 and Figure 7. The differences created by this filtering process to remove noise are clearly shown. As shown in Equation 6, the size of the kernel matrix of the median filter was determined as 5x5 as a result of noise measurements. This kernel size was determined by analyzing the noise on the images.

$$K = \begin{vmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{vmatrix} \quad (6)$$

2.2 Template Matching

After removing noise from the image, image processing algorithms were applied. In image processing, there are multiple approaches and methods to evaluate a fragment independently from the whole image from which it was extracted and to identify the object in its content. One of the main methods of object detection is Template Matching. This algorithm uses a sliding window method to overlay a template on the weld image and detect similar points on the this image. The template is overlaid on the weld image at coordinates (0,0), all pixels are individually shifted and matched, a similarity ratio is generated according to the similarity method used, and if the template is combined with the existing part of the image, it returns those pixels as a result. Based on the similarity ratios of the pixels and by choosing a threshold value for these ratios, objects in the image can be identified. The threshold helps to ignore pixel similarity that holds redundant information and find the results accurately [13].

This method is a technique in digital image processing for finding small parts of an image that match the template image. It can be used in manufacturing as part of quality control, as a way to navigate a mobile robot, or as a way to detect edges in images. Although the accuracy of this method is high, the computational load is quite high. In fact, with today's hardware, it is very difficult to implement without using acceleration techniques. When it comes to tracking an object, the processing needs to be done in real time. This requires very fast hardware and algorithms. In computer vision applications, it is very difficult to track an object in nature in real time [14]. Object tracking involves estimating the trajectory of an object moving in consecutive frames. Dynamic variables such as the features that denote objects, the motion and temporal changes of objects, or the exact addition of the tracked object need to be considered in tracking [15]. This monograph describes methods and systems for object tracking systems, as well as object tracking system structure and the development of new trends in proposed systems. In another study on weld tracking, although images in nature are 3-dimensional, the resulting images are 2-dimensional, there is noise in the image, and there are complete object overlaps, the presence of complex object shapes, the presence of irregular or fragmented objects, and the disadvantages of object tracking because the movements of the objects can be complex and partial has been investigated [16, 17]. Changes in image brightness, real-time application needs, and shadows from moving objects make object tracking complex [18]. These complexities make it difficult to dynamically track objects. Template matching is less affected by the above disadvantages than most algorithms. The main challenges in this algorithm are: occlusion, detection of non-strict transformations, illumination, background changes, background clutter and scale changes. In this study, the shape matching algorithm is used to extract various weld seam features. In the algorithm, firstly, a filter is applied to the gray level images and Canny algorithm is used to identify the points of weld where edges are found. With Template Matching, these points are compared with the features in the target image to determine the types of welds or the extent to which spot welds are made correctly. With template matching, it is aimed to make the decision-making mechanism faster and more accurate while the robot is working.

Although it is difficult to recognize the welding environment, we are only interested in the starting position of the weld seam. Searching only for the position of interest is a practical method. Template matching is the process of comparing the position in an image and the intensity values in the template with the corresponding values in the image to determine its presence at that point and place the template in an appropriate position. This principle meets the requirements of initial weld location recognition, which avoids complex recognition of the entire environment of weld. In fact, an exact match of intensity values is rare. A measure of difference between the intensity values of the template and the corresponding values of the image is required. By setting a threshold value, we can look for similarity higher than a given value. Therefore, there is no need for a precise analogy. The similarity ratio can be derived as in equation 7.

$$R(i,j) = \sum_{m=1}^{M}\sum_{n=1}^{M}[s^{i,j}(m,n) * T(m,n)] \,/\, \sum_{m=1}^{M}\sum_{n=1}^{M}[s^{i,j}(m,n)]^2 \tag{7}$$

Where s is the weld image, si,j is the searched image, T is the template image, i and j are the column and row values in an image [8].

Figure 8. Used Templates

Figure 8 shows the templates used. By selecting more than one template, we aim to avoid data loss and find more matches. Three of these templates represent a good weld and one represents a bad weld. In this way, it is aimed to detect both good and bad types of welds.

Figure 9 shows how the algorithm works. As can be seen, the ROI is first selected and then the image preprocessing step is applied. In this step, a filter was determined according to the type of noise. Then, it is decided whether to apply edge detection to the images according to whether the cake molds in the images are colored or not. Finally, the Template Matching algorithm was applied.

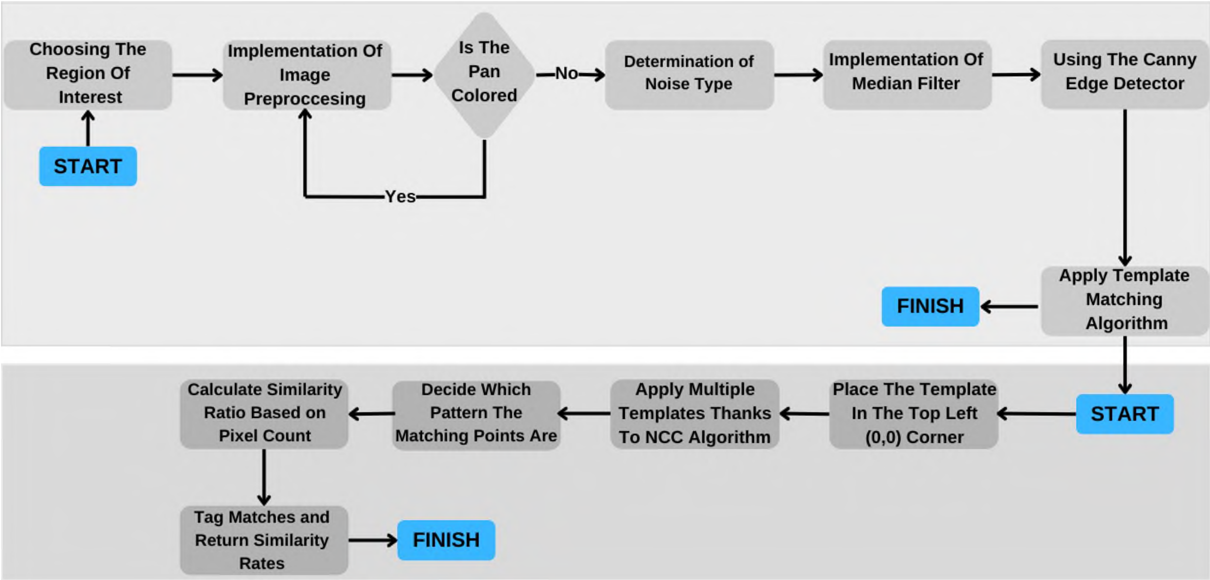

Figure 9. Algorithm's Flow Diagram

2.3 Normalized Cross Correlation

Since the processing load is quite high in the template matching algorithm, the algorithm runs slowly. For this reason, various types of algorithms have been created. In this study, normalized cross correlation (NCC), one of these algorithms, is used.

The Template Matching algorithm is classified into area-based and feature-based algorithms. In feature-based algorithms, edge, corner, shape and texture features of objects in the template are extracted and this information is searched for in the next frame. Given a template T = nXn and a weld image S = mXm, the pixels of T are denoted by T(i, j), the pixels of S are denoted by S(i, j), r = {0,1, ..., m-n} and c = {0,1, ..., m-n}, the progression in row is denoted by r and the progression in column is denoted by c. The general equation of the NCC algorithm is in equation 8.

$$\mathrm{NCC}(r,c) = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n}[S(i+r,j+c)-\bar{S}(i,j)][T(i,j)-\bar{T}]}{\sqrt{\sum_{j=1}^{n}\sum_{i=1}^{n}\left[S^2(i+r,j+c)-n^2\overline{S}^2(i,j)\right]\sum_{j=1}^{n}\sum_{j=1}^{n}\left[T^2(i,j)-n^2\overline{T}^2\right]}} \tag{8}$$

In the NCC algorithm, NCC(r,c) takes values between -1 and 1. If NCC(r,c) takes the value 1, matching occurs, if it takes the value -1, reverse matching occurs. For a match to occur, the value must be close to 1 [20].

3. RESULTS and RECOMMANDATIONS

In this study, an algorithm was developed to measure how similar the weld regions are to the specified templates and to improve time consumption and performance. According to the results obtained, the torch tip periodically overheats and becomes irritated over time, which causes deterioration in the welding process. It has also been observed that some welds slip because of incorrect initial positioning of the torch tip. Weld coordinates determined by the algorithm can be used to eliminate this shift. The proposed feature extraction algorithm processes images at an average of 200 ms according to the data obtained from image processing and obtains the result. This time can be considered good compared to the average welding speed. It was also observed that as the size of the processed image decreased, the time it took for the algorithm to respond decreased. When we process all the cake molds used in the application, the time taken is around 1500 ms, while focusing on small pieces, the time taken decreases to around 500 ms. The use of ROI has been found to be beneficial at this point. Thanks to the image preprocessing steps and the NCC algorithm, this time was reduced from 350 ms to around 200 ms.

Also with the method used in the experimental study, 784 welding points were examined. Images were taken from the weld environment after the robot finished its operations. Therefore, there is noise in the images. In this experiment, the images were first reduced to gray level and then a median filter was applied. The purpose of gray level reduction is to ensure that an edge detection algorithm is applied to the images, and the purpose of the median filter application is to eliminate noise. According to the results obtained from the noise analysis, a filter with a 5x5 kernel matrix was applied. Then, edges in the image were extracted using an edge detection algorithm that can be used for colored pans. Then, the weld images made with the Template Matching algorithm were detected. While the weld detection rate was on average 60% - 65% in images without preprocessing, this average increased to around 75% in images with image preprocessing. Again, detection rates increased from around 50% per image to 75%.

Table 1. The Answers of Noise in Images to Different Masks

Matrix Size	Noise Value
Unmasked Image	1.61688
Masked Image with a 3x3 Kernel	0.59702
Masked Image with a 5x5 Kernel	0.52164
Masked Image with a 7x7 Kernel	0.44577

Table 1 shows the results of the analysis for noise. Noise analysis results are shown for unmasked or masked images with various kernel matrix sizes. In the light of these results, noise decreased as the mask size increased. However, as the mask value increases, it is seen that the details in the image are lost. For this reason, the ideal mask size was determined as 5x5.

Figure 10. Result of Image Preprocessing

As shown in Figure 10, in the shadow of the results obtained, the results of the median filtered images give very useful results in terms of pre-processing compared to the results of the unfiltered images.

The threshold determined by the Otsu function can accurately binarize the weld region and the weld pattern. This is because the grayscale histogram of the weld region shows different features due to its differences with the original image. Of the two peaks, one peak represents the weld region and the other the background. In this way, the threshold selection is completed automatically. For each image, different thresholds are set according to the difference between the peaks in the histograms of the background and the weld region to reduce data loss as much as possible.

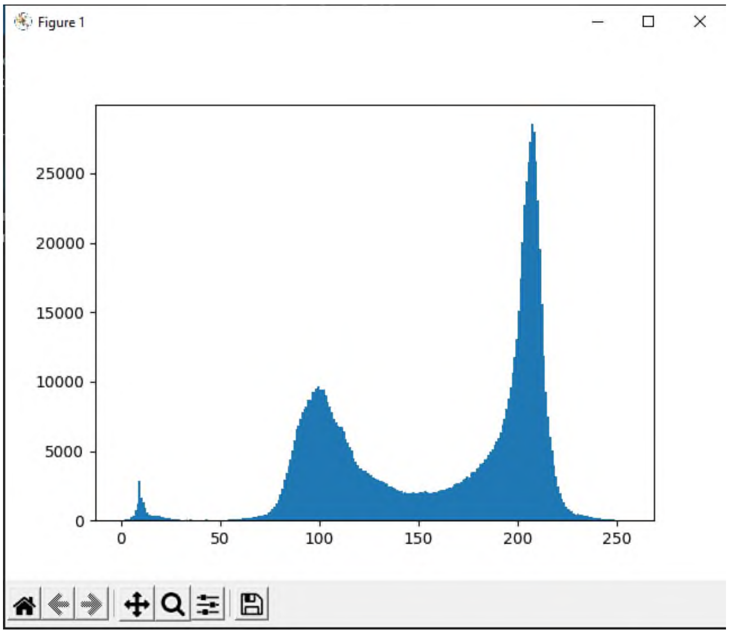

Figure 11. Histogram of the Original Image

As shown in Figure 11, images contain two peaks in histogram charts. Low peak welding zone and high peak background cake mold. In this way, a threshold to be determined in the region between the two peaks was to distinguish between the weld region and the cake mold.

Grey-leveled reduced images are given as input to the Otsu function for automatic threshold of images. Thus, there is no need to re-adjust the threshold for each image. It is recommended to reduce the images to gray level for auto-squeezing. This makes it easier to process cake pans produced in different colors. Template matching cannot be done correctly without graying dark pans. When images reduced to gray level were given as inputs to the Otsu function, the threshold values were determined to be 0.45 on average. Since the specified threshold value is very low, the use of the function cannot be recommended for the images used in Otsu. It is aimed to prevent data loss with the threshold value determined separately for each image [22].

Weld tracking was done by showing side weld trace lines and edge removal errors and finding the centers of these lines. Again, to acquire the weld seams, the acquisition of the weld center and laser strips by row scanning and column scanning respectively has been removed. As another example, a precise Hough program was programmed to extract the seam center. Another study proposed a two-process feature extraction method to detect the center of fillet weld seam [19]. While the edge detection algorithm used in this study gave good results in finding the edges of the weld points, it detected edges at different points affected by the lighting conditions.

In addition, the Canny edge detection algorithm was used to detect the weld points of different colored cake pans. Figure 12 shows the results of the edge detection algorithm. As can be seen in this way, the algorithm has accepted many unnecessary details as edges. Because the center of

the mold was hollow, the reflected light was detected as an edge. To overcome this problem, the mold must be vertically illuminated with an external light weld.

As a result of the study, Template Matching algorithm applied after image thresholding, gray level reduction and image preprocessing steps, the points of weld were detected. Detection rates were found depending on the similarity of the template and the weld point. Here, features of the templates such as texture and shape were utilized. These results may vary depending on the condition of the torch tip, the intensity and direction of the light. However, the results show that matches were mostly achieved. The matching results can be improved by obtaining the templates under better conditions and increasing the number of templates. In this way, the number and quality of matches obtained can be increased.

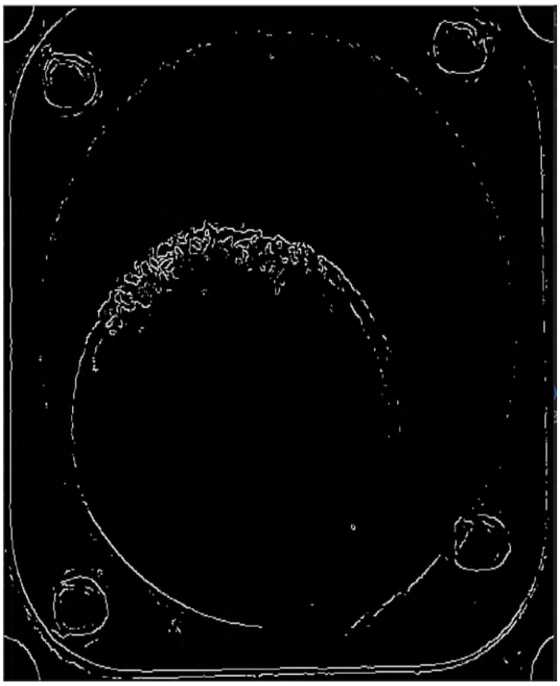

Figure 12. Result of Canny Edge Detection Algorithm

In addition to measuring how similar the welds are to the templates, it is also aimed to determine the type of weld. It was observed that spot type welds and I type welds could be distinguished from each other. In this way, various weld types can be distinguished and parameter settings can be adjusted according to that weld.

Figure 13. Weld Image of a Degraded Welding Torch Tip

Figure 13 shows how a deteriorating weld tip affects weld location and weld type. In the results shown here, the number of welds detected decreases and the locations where the weld point is sought vary considerably.

Figure 14. Shifted Weld Image

As shown in Figure 14, positions that may be important in detecting shifted and distorted weld points were obtained. Shifting of weld areas due to incorrect positioning makes weld detection impossible. This positioning error causes significant distortion of the weld shape. The detected coordinates can be given as feedback to the robot by taking the difference between where the welds should be and where they are and can be used for correction or maintenance purposes.

Weld points found with different templates are shown in different colors. As can be seen from the results, the goal of reducing data loss was achieved by finding the weld points with various templates. The number of templates can be increased or decreased. If the number of templates is increased, data loss will decrease, but the algorithm will take longer to run. This situation should be evaluated and decided according to the requirements. Also a template for bad weld types is defined in this application. The detection rate of bad welds can be increased by increasing the number of templates defined for bad weld points.

Figure 15. Template Matching Algorithm Results

As seen in Figure 15, the welds are not always aligned or where they should be. In such cases, the coordinates of the welds must be determined precisely and the place to be searched.

Figure 16. Result obtained with Median Filtered Image

As can be seen in Figure 16, the incorrectly detected results in the Median Filter applied image have been canceled. In addition, the accuracy of the correctly detected point of weld has increased. This can be inferred from the increase in the threshold value. Here, the threshold value is close to 74%, indicating that the filtering process can give more accurate results.

Figure 17. Template Matching Algorithm Results

In Figure 17, the quality of detection is erroneously degraded in the unfiltered image. Here the threshold value approached 60%.

Figure 18. Template Matching Algorithm Results

Figure 18 shows the results of the template matching algorithm applied to unfiltered weld images. Again, as seen in Figure 11, when no filtering is performed, the location of the points detected with the match rate values are labeled. Since no filter is applied here, the similarity rate has dropped significantly.

Table 2. Number of Templates Detected in the Data Set

		Number of Detections in Images without Image Preprocessing				Number of Welds Identified	Number of Detected Images With Image Preprocessing				Image Preprocessed Images Number of Detections
Number of Templates Detected at Various Thresholds in 784 Images Used	Threshold Values	Templates 1	Templates 2	Templates 3	Templates 4	Total	Templates 1	Templates 2	Templates 3	Templates 4	Total
	0.45	105	94	176	59	434	111	101	193	64	469
	0.60	98	88	169	56	411	109	97	187	62	455
	0.70	94	85	162	55	396	107	94	182	61	444
	0.75	90	81	155	53	379	104	92	179	60	435

As can be seen in Table 2, more templates were detected in the images with image preprocessing. Accordingly, it can be said that the study works more effectively. It was also observed that the number of detected points decreased as the threshold value increased. Therefore, it was also determined that the accuracy of the algorithm increased. In this study, 784 points of weld were used as the data set.

Table 3. Similarity Percentages of Templates Detected Without Applying Image Preprocessing Step to the Images in the Dataset

Template Name	Number of Templates	Number of Detections				Percentage of Detections			
Threshold Values		0.45	0.60	0.70	0.75	0.45	0.60	0.70	0.75
Template 1	149	105	98	94	90	%70.4	%65.7	%63	%60.4
Template 2	130	94	88	85	81	%72.3	%67.6	%65.3	%62.3
Template 3	292	176	169	162	155	%60.2	%57.8	%55.4	%53
Template 4	213	59	56	55	53	%27.6	%26.2	%25.8	%24.8

Table 3 shows the results of the study performed on images without the image preprocessing stage. According to these results, similarity remained at low levels. The reason for this is that images containing noise negatively affect the algorithm. The template that the welds would resemble was determined with the help of the operator. The reason why the detection rates of welds in the group called faulty welds are low is that there are many different types of faulty welds, but a template is specified. These percentages can be increased by increasing the number of welds templates of the wrong type.

Table 4. Similarity Percentages of Templates After Applying the Image Preprocessing Step to the Images in the Dataset

Template Name	Number of Templates	Number of Detections				Percentage of Detections			
Threshold Values		0.45	0.60	0.70	0.75	0.45	0.60	0.70	0.75
Template 1	149	111	109	107	104	%74.5	%73.1	%71.8	%69.8
Template 2	130	101	97	94	92	%77.7	%74.6	%72.3	%70.7
Template 3	292	193	187	182	179	%66.1	%64	%62.3	%61.3
Template 4	213	64	62	61	60	%30	%29.1	%28.6	%28.1

Table 4 shows the similarity results obtained from the images with image preprocessing. According to these results, there is an increase in detection rates in the images with image preprocessing. Again, detection rates can be increased by increasing the number of templates.

Table 5. Parameters of the Algorithm

Parameter	Values
Threshold	0.7
Average Algorithm Time (ms)	189,90
Size of Median Filter's Kernel Matrix	5x5

Table 5 shows some parameters of the algorithm used. The threshold value that gives the most positive results is 0.7. Here, the most effective threshold value that does not cause false weld detection was selected as the criterion. The average algorithm time was 189.9. The average time of the algorithm is the average of the times spent in each iteration. This result was achieved with the AMD Ryzen 7 5600 processor. Depending on the type of images, the most appropriate median filter kernel was selected as 5x5. The median filter kernel matrix was determined taking into account the results from the noise analysis shown in Table 1 and the fact that image blurriness increases as the matrix increases.

In line with the results obtained in the study, the high algorithm time due to the high computational load, which is one of the most important disadvantages of the Template Matching algorithm, has been overcome with the NCC Template Matching method. In this way, the application is optimized for high speeds in industrial environments. In addition, various image preprocessing and edge detection steps have been applied to reduce the impact of the harsh conditions of industrial environments. The success rate is increased by using multiple templates.

The labeled images resulting from this study can be used as a healthy dataset for machine learning algorithms in the future. In addition, they can be given as input to predictive maintenance algorithms and maintenance dates can be calculated.

Figure 19. Template Matching Algorithm Results Applied to Different Weld Types [21]

With this method, different weld types can be distinguished from each other as well as spot weld types. Figure 19 shows us that the type of weld made in the form of I type has been determined. Figure 19 shows the detection of type I weld with the Template Matching algorithm. From this point of view, it is also possible to detect I, U and V type welds. It is aimed to apply parameter changes by reacting instantaneously to the changing weld shape during welding [22].

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