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# Autonomous recognition of Weld seam in 3D for robotic path planning

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**Abstract**
Most of the welding robots are programmed to weld specific workpieces through 'teach and playback' method. To accommodate a variety of work pieces, the operator has to reprogram the robot for specific parts manually. This problem of reprogramming for each work piece can be obviated by utilizing vision based path planning. This paper presents an image processing method to recognize the seam in 3D from a single image. The background is eliminated through a novel algorithm proposed. The image coordinates of the seam recognized are quickly transformed into 3D world coordinates through an improved polynomial regression model. The effectiveness of the algorithm is validated by comparing with the CMM measurements. The results proved that the proposed method is capable of recognizing the seam even in the presence of illumination errors like glare, shadows, etc. Furthermore the proposed algorithm can detect the seam in curved surfaces as well as in flat surfaces.
Keywords: Robotic Welding, Machine vision, Weld seam recognition, Image processing, passive sensing.

## 1 Introduction

Robots are being deployed in industrial operations for the past two decades, but the processes in which robots are deployed are usually repetitive in nature. Welding robots are typically programmed to carry out the welding process for a specific component which means limited flexibility to accommodate different sets of work pieces. While this approach of programming for the specific component is justified in case of mass production, for 'low to medium' production and in case of repair works, it essentially leads to reprogramming the robot for each component belonging to a unique part-family.

To eliminate this disadvantage of human intervention, the robots are increasingly relying on usage of vision [1]. Nowadays a lot of research is being done to integrate vision in robot manipulators. This allows for accommodation of different types of work piece being operated by Robots. The vision system can be classified into two different types namely, Active vision sensing and Passive vision sensing.

In Active vision sensing, an external light source is used to illuminate the scene being captured while in case of passive vision sensing, no external source is used to capture the scene. The different active vision sensors used in Robotic are welding are LASER [2, 3], Structured light sensors [4, 5], and Arc sensors [6]. Active vision sensors are mainly used in operations pertaining to mass production since the initial cost is quite expensive. While this cost is justifiable in industries which process high volume of materials, the smaller industries often view it untenable to implement vision sensors.

Seam detection through passive vision sensors is an active research area [7, 8, 9, 10, and 11]. One of the major drawbacks is that the majority of the passive vision sensors are used to provide only 2D information about the seam to be welded. 2D vision is inadequate for the welding as the depth perception is required in practical applications. For example, in Gas Metal Arc Welding (GTAW) the depth of fusion has a direct correlation with Contact Tip and Work Distance (CTWD).

Stereoscopy [9, 10, 11, and 12] is used to obtain the 3D information of the weld seam using passive vision sensors. This is carried out by taking the picture of the scene from two different perspectives and extracting the depth information by triangulating them. The main disadvantage of utilizing the stereoscope is that it is unreliable if there is no texture in the image, which is often the case when it comes to work pieces made of ferrous materials. Furthermore illumination errors like glare and non uniform illumination makes the stereo matching very difficult.

Furthermore, most of research carried out using passive vision sensors is for recognizing seams on a single plane [7, 10] which severely limits the scope of implementing it in a diverse environment where flexibility is a big expectation.

There is also research carried out to determine the seam from a single image [8]. While the method suggested by the author is able to identify the seam quicker than the stereoscopy, this also comes with a tradeoff that it can only identify the 2D coordinates of the seam.

In order to identify the seam in an image several techniques are being employed such as global and local search. One quick way of eliminating the background is through employing a predefined Region of Interest (ROI) and only focusing on that ROI by disregarding any objects outside of it. This assumes the weldment will take up certain predefined position in the welding set up. In [11, 12], the weldment is assumed to be at the center. While it is very quick to eliminate the background, it stipulates that the manual intervention is often needed to ensure the weldment to be within the ROI, which is not always possible in repair works.

Chen et al [13] separated the weldment from the background through subtraction of the scene containing the weldment with the default background image. This is a computationally intensive process as the subtraction of the pixel values between the two images will require taking two shots from the same camera angle.

Mitchell Dinham et al [7] have used a search window based on the Hough transform to detect the weldment directly from a both right and left hand image separately before extracting depth using stereo matching based on 2D homography technique. This approach is only useful to determine the weld

seams in flat surface and cannot be applied to determine the 3D pose of weld seam in curved surfaces.
A composite sensor system is used to detect the seam, as proposed by Xu et al [6], consisting of the visual sensor (passive) and arc sensor. In addition to identifying the seam, the passive vision sensors [14-19] are also used in tracking it during the weld seam process for real time control.
The objective of this work is to automatically identify the weld seams in flat as well as curved surfaces, without assuming any prior knowledge about the seam, from a single image to achieve the path planning of the robot in real-time. A novel method of identifying the seam is proposed. After determining the image coordinates of the seam [i, j], the world coordinates are computed quickly by using an improved regression method. The performance of the proposed method is evaluated by comparing the predicted coordinates of the seam with actual coordinates measured by CMM. The results show that the proposed method is capable of determining 3D coordinates of the seam in real time compatible for the welding application. Although this algorithm is perfectly capable of identifying seams in flat surfaces, the procedure is illustrated only for seams in curved surfaces in this paper. The paper is organized as follows: In section 2, the methodology is described. Accuracy of the algorithm is discussed in section 3. Finally the conclusion is given in the section 4.

## 2 Methodology

### *2.1 Process Overview*

This project autonomously determines 3D coordinates of the weld seam through by first identifying the image coordinates of the seam and transforming it to world coordinates by a Mathematical model for guiding the welding robot. All the following steps are executed in MATLAB 2012 b [20]. The steps involved are as follows:

- Camera is calibrated using a reference object of known dimension. This establishes a mathematical model between the image-coordinates and the world coordinate.
- Scene comprising the weldment is acquired using a USB 2.0 Web camera
- Preprocessing is carried out to reduce the noise and sharpen the edges in the image.
- Background is eliminated through blob analysis to extract the workpiece separately.
- Continuous weld seam is obtained through morphological operations like dilation and erosion.
- Image coordinates of the weld seam are transformed to the world coordinates using the polynomial regression model. Thus the seam coordinates are obtained from a monocular image at high speed. The coordinates are transformed with respect to end effector from the camera

The figure 1 illustrates the procedure of the aforementioned algorithm.

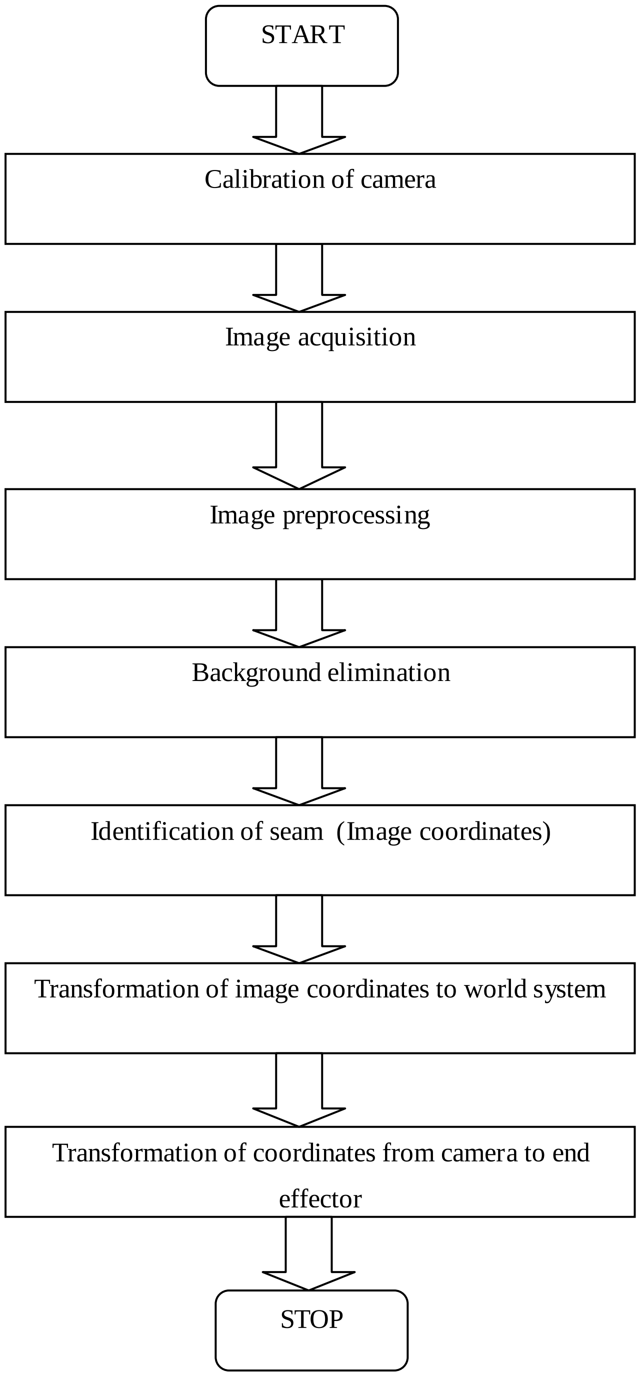


**Figure 1 Process Flow**

### *2.2 Calibration of camera:*

The camera is calibrated to establish a mathematical relationship between image points and the world coordinates. The process of the transforming the image coordinates to the world coordinates is done through Least square polynomial regression. This project utilizes the 'fast and robust calibration technique' suggested by [21] to obtain the world coordinates of the weld seam. A cuboid of known dimension is chosen as reference object as shown in the figure 10. Five control points are chosen to establish the relationship between the image points and the world coordinates. The correlation coefficient is determined through the bivariate quadratic polynomial model. This correlation coefficient is used to obtain the world coordinates of the seam [X, Y, Z] for the seam [i, j] determined in section 2.6.2.

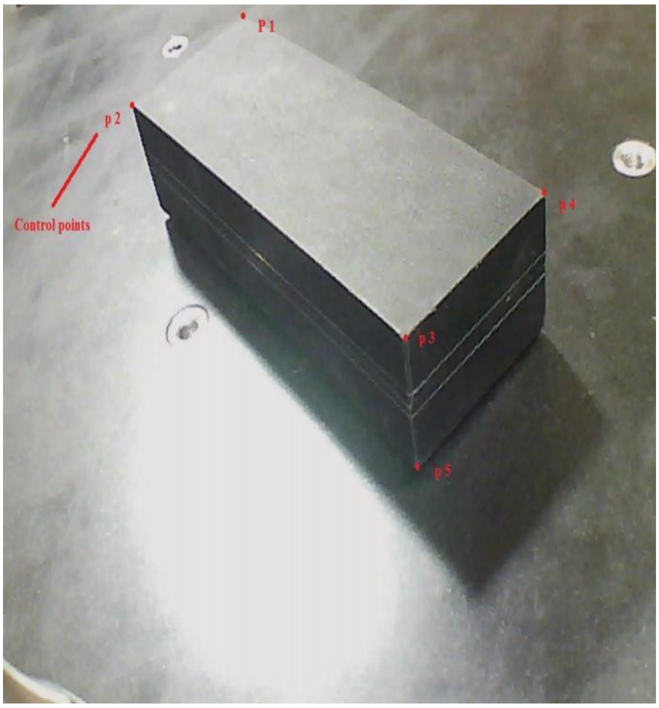


**Figure 2 Reference object chosen for calibration with chosen control points**

The dependent variable can be determined from the independent variable by decomposing the input data into least square linear regression model. A quadratic polynomial model is chosen, as the weld seam data are that nature, to give optimal results for the experiments conducted and model is proved to be appropriate through the estimated goodness of fit. The equations (1 to 8) are adopted from [21].

$K=\alpha_0+\alpha_1 B+\alpha_2 B^2$ (1)

Where,

K-Output variable

B-Input variable

$\alpha_0$, $\alpha_1$, $\alpha_2$- Coefficient matrices.

$W= \alpha_0+\alpha_1 i+\alpha_2 j+\alpha_3 i^2+\alpha_4 ij+\alpha_5 j^2$ (2)

Extending the same equation for two variables,

Where,

W- World coordinates

i, j- Image coordinate

$\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ – Coefficient matrices

Through calibration, the values of the coefficient matrix are determined. As the control points in the reference object is of known real world coordinates and image points (i, j), it is used to compute the coefficient matrix. The accuracy of the calibration depends very much on the accuracy of the image points (i, j) of the control points.

***2.2.1 Determination of the Correlation Coefficients:***

The generalized equation for bivariate polynomial regression is expressed in matrix form as,

$[X]=[Image].[\alpha_x]$ (3)

$[Y]=[Image].[\alpha_y]$ (4)

$[Z]=[Image].[\alpha_z]$ (5)

Where,

$$[Image]=\begin{pmatrix} 1 & i_1 & i_1^2 & j_1 & j_1^2 & i_1j_1 \\ 1 & i_2 & i_2^2 & j_2 & j_2^2 & i_2j_2 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 1 & i_n & i_n^2 & j_n & j_n^2 & i_nj_n \end{pmatrix} \left( {}_{n \times 6} \right)$$

i, j – Image points.

$\alpha_x = [Image^T\, Image]^{-1} [Image^T] [X]$ (6)

$\alpha_y = [Image^T\, Image]^{-1} [Image^T] [Y]$ (7)

$\alpha_z = [Image^T\, Image]^{-1} [Image^T] [Z]$ (8)

Through the above equations (6, 7, 8) the correlation coefficients for all six polynomial terms are determined through which the image points of the seam [i, j] are directly mapped onto world system at a very high speed.

***2.3 Image acquisition:***

The images are taken with a charge-coupled device (CCD) camera having 0.8 Megapixels and Image resolution 1024 × 768. The focal length of the camera is 3mm. The scene containing the welding assembly, which is shown in the figure 3 (A), is captured using an iBall Webcam. The image captured at a typical factory environment where the proper illumination cannot be ensured.

***2.4 Preprocessing:***

***2.4.1 RGB to Grayscale conversion:***

As the RGB image is tedious to process, the Image is converted from RGB to Grayscale in-order to reduce the computation burden.

***2.4.2 Median Filter:***

In order to reduce the noises in the background, median filter is applied iteratively. The median filter is selected over Gaussian filter as it reduces only the noise leaving the edges intact. A neighborhood window of 3*3 is chosen.It is found that applying the median filter at least four times gives the optimal result.

***2.4.3 Image sharpening:***

To facilitate the identification of the weld seam, the edges are sharpened using Unsharp filters. It involves subtraction of the image from its blurred version. This step is vital as it enhances the edge sharpness and makes the adaptive thresholding very easier. The steps involved in image sharpening are,

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a. Application of Gaussian filters to obtain blurred version of the image.
b. Subtraction of blurred version of the image from the Image itself.
c. The result of the subtraction is added to the image itself.

All the processes involved in the preprocessing of the image are shown in the figure 3.

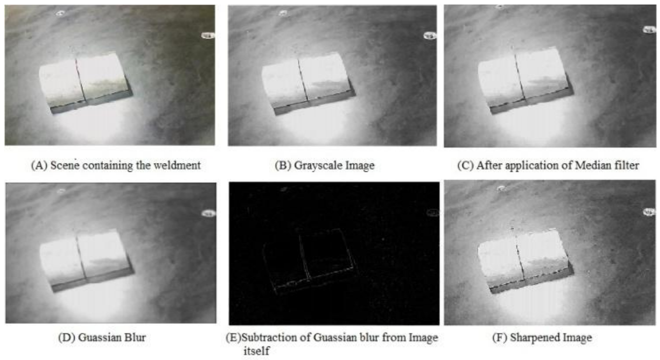


**Figure 3 Image Pre-processing**

***2.5 Background Subtraction:***

***2.5.1 Edge detection*:**

A Canny Edge detection algorithm [22] is used to determine the Edges in 2D images. The Canny algorithm is selected as it is better suited to detect the true edges for this application. The edges detected using the canny algorithm is shown in the figure 4 (A).

***2.5.2 Elimination of isolated objects:***

The small isolated objects are removed from the image by labelling [23] all the objects based on its connectivity to its neighbourhood and thresholding the objects of small area.
Threshold criteria is given as,

$$\text{Object}=\begin{cases} 1, \text{ if Object} >= T \\ 0, \text{ if Object} < T \end{cases}$$

Where, T= threshold
The image after the removal of the small objects is shown in the figure 4 (B).

***2.5.3 Applications of morphological operations to obtain continuous edges.***

Continuous edges are obtained by morphological operations dilation followed by erosion using the same structural element. The image obtained through the morphological operations is shown in the figure 4 (C).

***2.5.4 Workpiece separation from the background:***

The weld assembly is separated from the background through labeling [23] the connected objects in 8 neighborhoods and separating the labeled object with largest area as the work-pieces are predominantly bigger than other objects in the image captured.

```
For 1: Number of labelled objects
{
  If (A>= max area)
     A =1
  Else
     A= 0
}
```

Where,
A= labelled object.
The segmented weldment assembly is shown in the figure 4 (D).

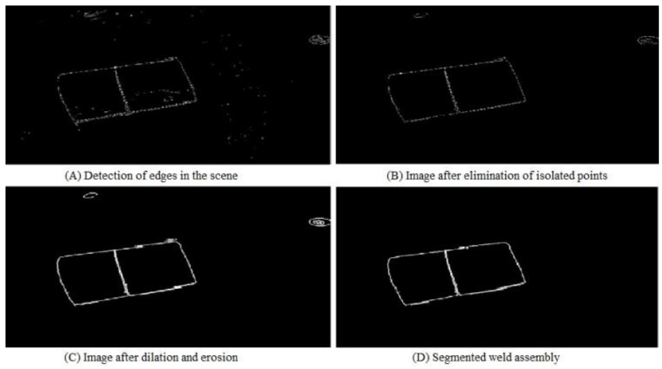


**Figure 4 Background subtraction**

***2.6 Identification of seam:***

The coordinates [i, j] of the seam are determined through the following steps,

***2.6.1 Elimination of outer boundary of the workpiece:***

The outer boundary of the workpiece is identified by through a contour tracing algorithm like Moore neighborhood or Radial sweep. The Moore neighborhood is used in this project for determining the outer boundary of the workpiece. Once the outer boundary pixels are identified, they are set to zero in the binary image through Logical indexing. The determined outer boundary of the weldment assembly is shown in the figure 5.

***2.6.2 Identification of weld seam:***

Once the outer boundary is removed, the seam is easily identifiable as it the longest continuous component in the image. Areas of all the remaining components are computed and filtered to retain only the component with largest continuous pixel count. It is further dilated and eroded to obtain a continuous seam. The final image after the morphological operations is shown in the figure 6.

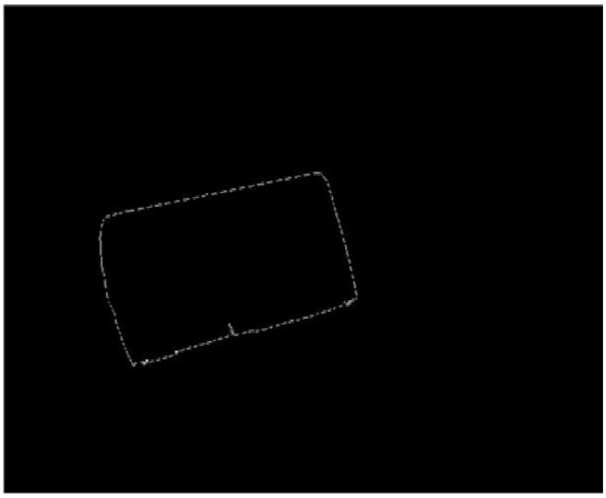

**Figure 5 Outer boundary of the workpiece**

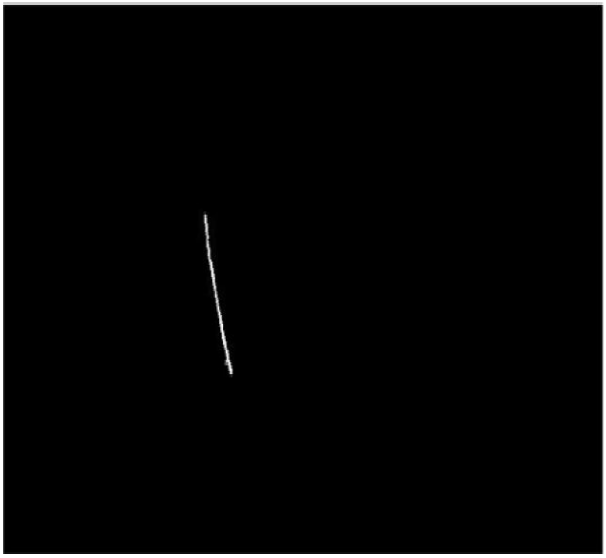

**Figure 6 Seam identified after morphological operations.**

***2.6.3 Determination of World coordinates from the Image coordinates of the seam***

The Image coordinates of the seam determined in the 2.6.2 section will be in the form of [i, j]. Through the mathematical model established by the camera calibration, the world coordinates are obtained as illustrated in the figure 7.The world coordinates are determined by transforming the image coordinates with the help of the correlation coefficients $\alpha_x$, $\alpha_y$, and $\alpha_z$ (from section 2.2.1) through the equations 3, 4, and 5.

Camera calibration using control points of the reference object

↓

Determination of the coefficient matrices $\alpha_{x,}$ $\alpha_{y,}$ $\alpha_z$ using [i,j] and [X,Y,Z] of the control points

↓

Image coordinates of the seam (i,j)

↓

Determination of world coordinates of the weld seam

**Figure 7 Steps involved in transforming the image coordinates of the seam to world system**

***2.6.4 Transformation of coordinates from camera to endeffector:***

The world coordinates determined are computed from camera as origin. In order to accomplish the path planning of the robot, the coordinate frames have to be transformed from camera to endeffector of the robot. This transformation of the frames is given by the equation 9.

$^{M}P_S = [T]^* [^{C}P_S]$ (9)

Where,

$^{M}P_S$ is the position of the seam from the manipulator

T is the transformation matrix of the coordinate frames

$^{C}P_S$ is the position of the seam from the camera

***2.6.5 Determination of smooth seam :***

As the End-effector can be programmed to trace only a smooth path, through Linear regression model, a curve of single pixel width fitting the pointcloud is determined as shown in the figure 8 (B).

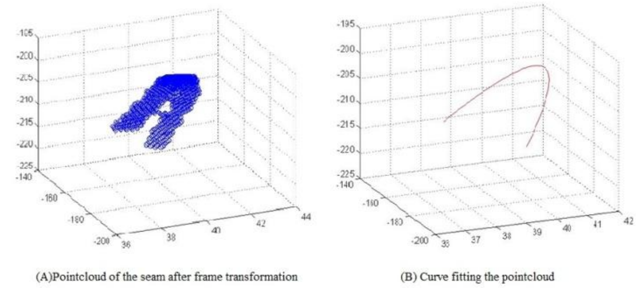


**Figure 8 Seam in World system**

## 3 Results:

### *3.1 Accuracy:*

The world coordinates of the seam are compared with Coordinate Measuring Machine values for the same profile. As the number of world points determined through the regression model is around 250 as opposed to ten data points obtained by a CMM probe of diameter 2mm, the values are plotted on a same graph to validate the accuracy. The data points in blue are the coordinates obtained through this algorithm, while the points in red correspond to the CMM measurement. Comparison between actual seam and predicted seam is shown in the figure 9 as follows,

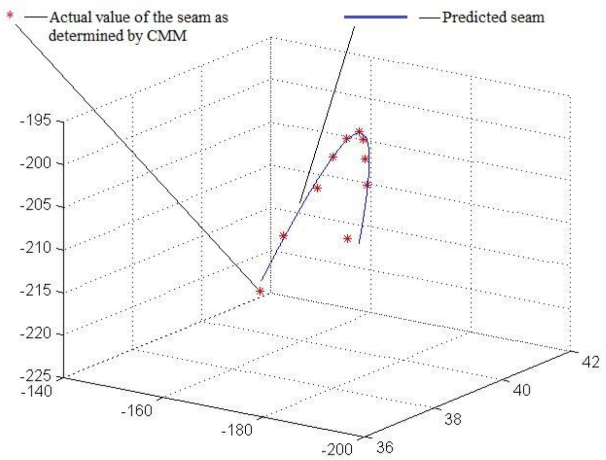


**Figure 9 Actual seam vs. predicted seam**

It can be inferred from the above plots that the values determined through this algorithm are in convergence with the actual values measured using the CMM. The Goodness of fit for the Bivariate linear regression model chosen is computed and the $R^2$ value is calculated as $R^2_x$ =99.99 %, $R^2_y$ =99.99 %, $R^2_z$ = 100 %.

## 4 Conclusions :

As understanding the vision in Industrial applications is inevitable to withstand in the competitive market, the balance between complete information and ease of processing the data has to be achieved. This project aims to combine the aforementioned features to achieve the trajectory planning of a welding robot quickly and at an economy

The main motivation of this project is about developing a novel algorithm to identify the Weld seam, present in curved surfaces, in 3D using a single camera for achieving autonomous identification of the seam, an approach that was rarely attempted before. The algorithm has the following features namely,

- Even in improper illumination (glare, shadows), the proposed method would yield desired results.
- It can detect seams in curved surfaces, as well as flat surfaces, using a passive vision sensor.
- Appropriate for real time welding as it is very quick**.**
- Unlike the stereoscopy, the results are very reliable regardless of the workpiece material, surface texture, etc.
- It can be further extended to other industrial applications like Bin picking applications, painting.

The algorithm also offers certain tradeoffs namely,

- The accuracy depends on the accuracy of the calibration. If the image coordinates [i, j] of the control points have to be very precise for accurate transformation of image to world coordinate system.
- Whenever the posture of the camera changes, it has to be recalibrated to obtain the coefficient matrix for that particular posture of the camera.

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