# Detection of Assembly Variations for Automatic Program Adaptation in Robotic Welding Systems

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## Abstract

This paper proposes a novel approach for detection of assembly variations to adapt the programming of a robotic welding system. A matching process is performed between the different parts of an assembly CAD model and a measured point cloud using an Iterative Closest Point algorithm to determine assembly variations. Experimental validation is performed with an industrial robot equipped with stereo camera and welding gun. A method for accurate calibration of sensor and welding gun is presented as it influences the quality of the welding process. Experimental results show an increased weld seam quality and the robustness of the proposed approach in industrial applications.

## 1 Introduction

Programming of robotic welding systems requires expert knowledge and is a time consuming task. This limits the cost-effective usage of welding robots in small and medium sized enterprises (SME) characterized by production of small lot sizes and high number of variants. Intensive research has been done on intuitive programming methods to reduce the programming time [1], [2]. However, a main drawback still is the need for precise fixturing and preparation of workpieces to enable a correct process execution with the once generated robot program [3]. To overcome this drawback, some approaches focus on seam tracking based on 2D laser sensors for real-time program adaptation [4], [5]. However, the adaptation strategy has to be reconfigured for each specific workpiece and is limited to simple workpiece geometries. Other approaches use computer vision to reconstruct the real workpiece geometry and automatically generate robot programs for each new part [6], [7]. Geometry reconstruction however needs complex computations and precise measurements. Other approaches focus on offline program generation based on the workpiece CAD model in combination with a precise object localization [8]. In this case, the workpiece can be registered using optical sensors to adapt the program to the actual workpiece location in the robot cell [3], [9]. Also force feedback sensing can be used for workpiece localization by determination of contact points between welding gun and weld part [10].

However, inaccuracies of upstream processes, like e.g. manual tack welding of the different parts, can result in variations between CAD model and the actual welding assembly. It is a fundamental problem in robot program planning based the workpiece CAD model, that these variations might be beyond acceptable limits for a correct execution of the manufacturing process [11].

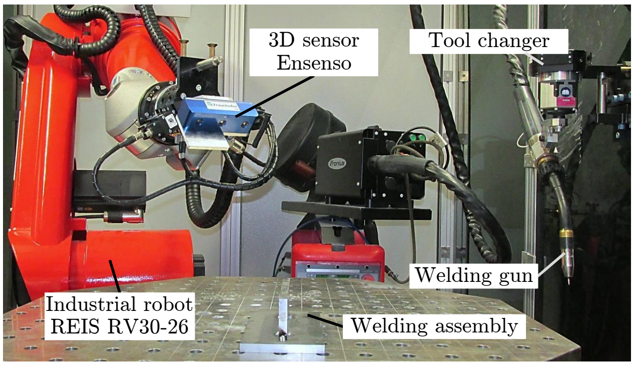


**Figure 1** Setup of robotic welding system.

In this paper, a novel approach is proposed to detect assembly variations for automatic adaptation of a robotic welding program. A matching process is performed between each part of an assembly CAD model and a measured 3D point cloud to determine relative part positions. An updated CAD model is automatically generated and used for subsequent program planning. Experimental validation is performed with an industrial robot equipped with stereo camera and welding gun, shown in **Figure 1**.

This paper is structured as follows: In Section 2, the approach for detection of assembly variations is presented.

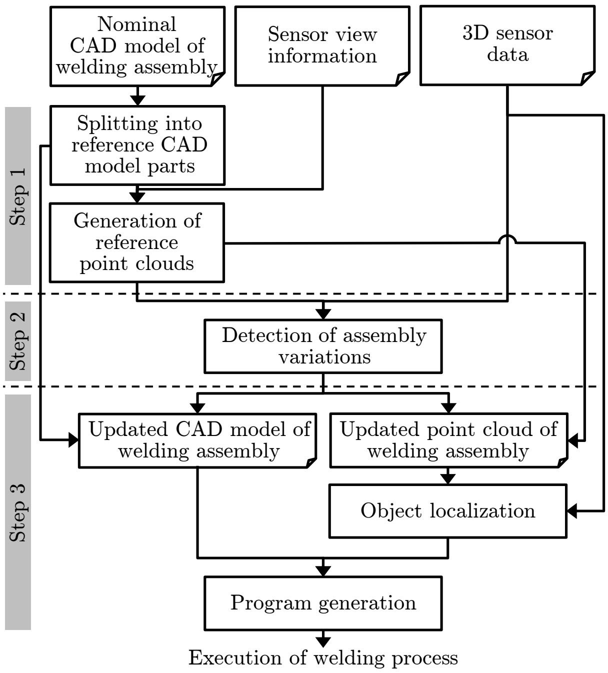


**Figure 2** Concept for detection of assembly variations.

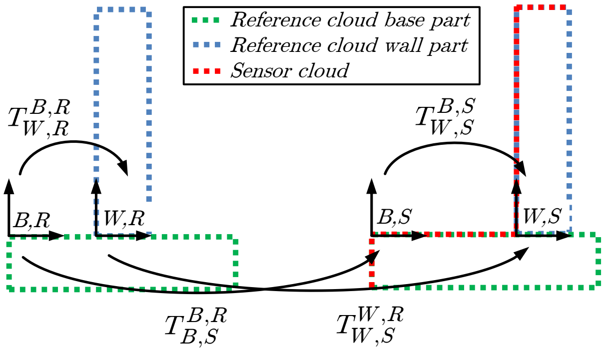


**Figure 3** Matching of reference point clouds with sensor point cloud for detection of assembly variations.

Section 3 presents implementation details of the approach. In Section 4, a method for accurate calibration of sensor and tool used in the experimental setup is presented. In Section 5, the proposed approach is validated by experiments on a real robotic welding process. Finally, conclusions are presented in Section 6.

## 2 Approach

The proposed approach for detection of assembly variations is shown in **Figure 2** and consists of three main steps. In step 1, the nominal CAD model of a welding assembly is splitted into its single part models. Additional information about sensor view field and direction is used to generate 3D point clouds of the respective parts. In step 2, a matching process is performed between each of the reference point clouds and a measured point cloud of the real assembly using an Iterative Closest Point (ICP) approach. Resulting rigid transformations are used for the detection of assembly variations. Finally in step 3, an updated point cloud of the welding assembly is generated for accurate workpiece localization. Moreover, an updated assembly CAD model is automatically generated according to the detected variations. This CAD model and the object localization results are then used for an accurate offline program generation.

Using the proposed approach minimizes the difference between real workpiece and its geometric model and hence enables a more accurate planning of the end effector trajectory along the weld part geometry and a precise workpiece localization. This results in an increased quality of the resulting weld seams. An additional advantage compared to classical online seam tracking with 2D sensors is the possibility to detect assembly variations without the need to actually measure the joint geometry itself. Sensor measurements can be performed on visible parts of the workpiece geometry. This clearly facilitates the programming for the measurement process. In SMEs it also enables production of workpieces with complex geometries that are not specifically designed for automated manufacturing and where the joint geometry is not visible with typical sensors.

The proposed approach only focuses on detection of assembly variations. The geometry of the single parts is assumed to correspond to the nominal CAD model. The detection of form deviations is not focus of this paper.

## 3 Implementation

The objective of the proposed approach is to detect assembly variations between a manufactured workpiece and its underlying CAD model. The assembly CAD data is represented in the STEP format supporting exchange of geometry data as well as information about the assembly structure. A fine mesh model of the different assembly parts with an average point distance of $q = 0.2\ mm$ is automatically generated from the CAD data using information about sensor view field and direction. Let $R_{Base} = \{\vec{r}_i\}$ and $R_{Wall} = \{\vec{r}_i\}$ be the reference point clouds derived from a CAD assembly with two parts (a base part and wall part) with the points $\vec{r}_i$ and $\vec{r}_j$ for $i = 1, \ldots, N_B$ and $j = 1, \ldots, N_W$.

With the 3D sensor mounted on the robot end effector, the geometry of the real welding assembly can be measured. The measured workpiece is represented by a sensor point cloud $S = \{\vec{r}_k\}$ with the points $\vec{r}_k$ for $k = 1, \ldots, N_S$. In order to align each reference point cloud $R_B$ and $R_W$ with the sensor point cloud $S$, a matching process is performed using the generalized ICP algorithm by [12], as schematically shown in **Figure 3**. It iteratively minimizes the sum of squared distances between corresponding points of two point clouds taking into account locally planar structure. As a result the rigid transformation between reference base cloud and sensor cloud $T_{B,S}^{B,R}$ and between reference wall cloud and sensor cloud $T_{W,S}^{W,R}$ can be obtained. These trans-

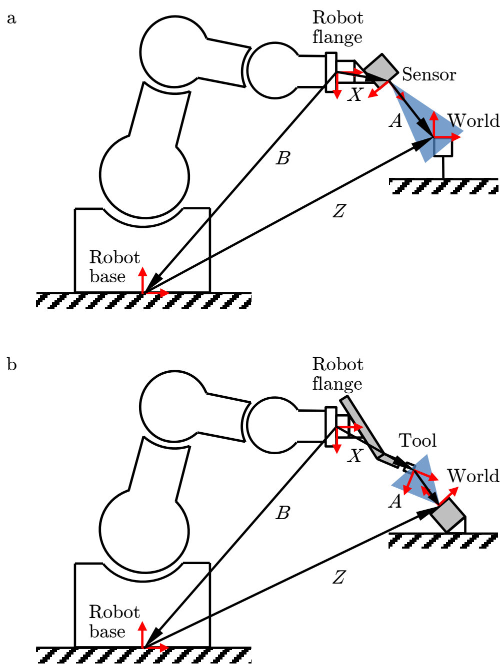


**Figure 4** Configurations for (a) sensor calibration and (b) tool calibration based on [15].

formations are then used to reassemble and update the assembly CAD model according to the detected variations. The assembly variation between base and wall part is expressed as a rigid transformation:

$$\begin{aligned} T_{AV} &= T_{W,S}^{B,S} \cdot inv(T_{W,R}^{B,R}) \\ &= inv(T_{B,S}^{B,R}) \cdot T_{W,R}^{B,R} \cdot T_{W,S}^{W,R} \cdot inv(T_{W,R}^{B,R}) \end{aligned} \tag{1}$$

with the nominal transformation $T_{W,R}^{B,R}$ retrieved from the workpiece CAD model and the transformation $T_{W,S}^{B,S}$ as a result of the point cloud matching. The resulting transformation $T_{AV}$ is then used to update the STEP file of the assembly as well as the corresponding reference point clouds $R_{Base}$ and $R_{Wall}$. The implementation can be easily extended for welding assemblies consisting of more than two parts by iteratively performing the matching procedure and update of CAD model and reference point clouds for each additional part.

# 4 Calibration of sensor and tool

In real applications, the performance of the proposed approach depends on an exact determination of the transformation between robot flange and sensor and between robot flange and welding tool. This problem is known as hand-eye or hand-tool calibration. The two configurations for sensor and tool calibration are shown in **Figure 4**.

The calibration method used in this paper is based on the work of [14] and [15] and allows for simultaneous calculation of transformations from robot base to world frame $Z$ and from robot flange frame to sensor or tool frame $X$. The calibration problem for both configurations can be formulated according to [15] as

$$AX = ZB \tag{2}$$

To find a solution, the robot can be moved in $i = 1,\ldots,N$ poses (position and orientation) resulting in different transformations $A_i$ and $B_i$. To obtain transformations $B_i$, the robot forward kinematics are used that can be retrieved directly from the robot controller. The absolute robot positioning accuracy however is typically not specified by the robot manufacturer.

The transformations $A_i$ are determined by measurements of a known geometry using a 3D sensor. In the case of sensor calibration (see **Figure 4** (a)), a fixed object is measured with the sensor mounted on the robot end effector. For the tool calibration (see **Figure 4** (b)), a measurement object is mounted on the tool tip and is measured by a 3D sensor that is fixed in the robot cell. The sensor z-accuracy for an average measurement distance of 370 $mm$ is specified with 0.131 $mm$. A matching process is performed between sensor point cloud and a point cloud derived from the measurement objects CAD model using a generalized ICP algorithm [12] as described in Section 3.

The proposed approach for detection of assembly variations is based on a precise workpiece localization. Thus, we focus on minimization of the position and orientation errors of the workpiece transformations $Z_i$ and reformulate Equation (2) as

$$Z_i = B_i^{-1} A_i X \tag{3}$$

Using Euler z-y-x convention, the workpiece position $t_{Z,i}$ and rotations $R_{Z,x_i}$, $R_{Z,y_i}$, $R_{Z,z_i}$ can be expressed as

$$Z_i = \begin{bmatrix} R_{Z,x_i} \cdot R_{Z,y_i} \cdot R_{Z,z_i} & t_Z \\ 0 & 1 \end{bmatrix} \tag{4}$$

To optimize for translational and rotational errors, we define respective error measures to be used in the calibration target function. The position error is defined as the norm of the vector that represents the difference between the translation vector $t_{Z,i}$ and an average translation vector $\bar{t}_Z$

$$E_{T,i} = |t_{Z,i} - \bar{t}_Z| \tag{5}$$

with $\bar{t}_Z = 1/n \sum_{i=1}^{N} (t_{Z,i})$. The orientation errors are defined separately for each rotation around the x-, y-, and z-axis. So the rotation error around the x-axis is defined as

$$E_{Rx,i} = |R_{Z,x_i} - \overline{R}_{Z,x}| \tag{6}$$

with $\overline{R}_{Z,x} = 1/n \sum_{i=1}^{N} (R_{Z,x_i})$ and assuming rotations to be small. Rotation errors around y-axis $E_{Ry,i}$ and z-axis $E_{Rz,i}$ are defined accordingly.

With these error functions, the calibration problem is defined by minimizing the following error vector:

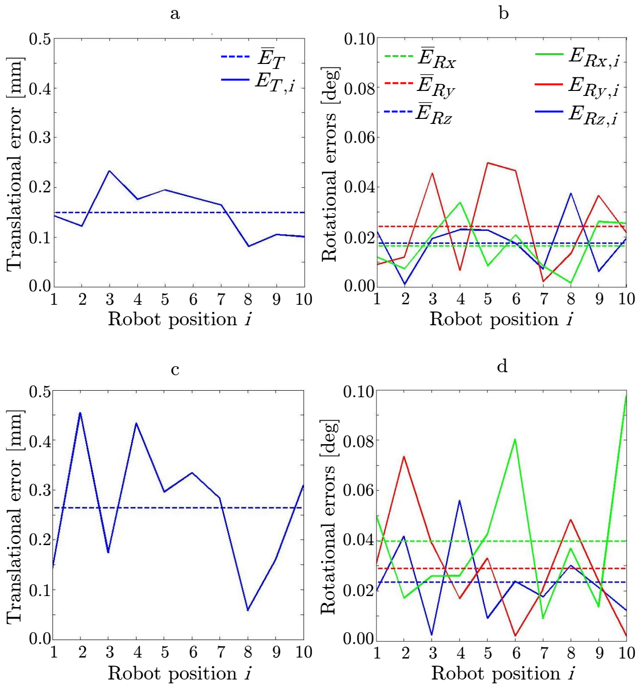


**Figure 5** Results of sensor calibration represented by (a) translation error and (b) rotation errors and tool calibration represented by (c) translation error and (d) rotation errors.

$$\min f(E_T, E_{Rx}, E_{Ry}, E_{Rz}) = \sum_{i=1}^{n} [E_{T,i}, E_{Rx,i}, E_{Ry,i}, E_{Rz,i}] \tag{7}$$

To solve this non-linear least-square optimization problem, the efficient Levenberg-Marquardt-Fletcher method [13] is used. The calibration procedure is tested for $i = 10$ different robot poses $B_i$ and according sensor measurements $A_i$. The average translation error $\overline{E}_t = 1/n\sum_{i=1}^{N}(E_{t,i})$ and average rotation errors $\overline{E}_{Rx} = 1/n\sum_{i=1}^{N}(E_{Rx,i})$ (for $\overline{E}_{Ry}$ and $\overline{E}_{Rz}$ accordingly) are calculated as measures for the overall calibration accuracy. The results for the sensor calibration are shown in **Figure 5** (a) and (b). The average position error is $\overline{E}_{T,Sens} = 0.1499\ mm$. Average rotation errors are $\overline{E}_{Rx,Sens} = 0.0164°$, $\overline{E}_{Ry,Sens} = 0.0243°$, $\overline{E}_{Rz,Sens} = 0.0176°$. Results of the calibration of the welding gun are shown in **Figure 5** (c) and (d). The average position error is $\overline{E}_{T,Tool} = 0.2642\ mm$. Average rotation errors are $\overline{E}_{Rx,Tool} = 0.0398°$, $\overline{E}_{Ry,Tool} = 0.0289°$, $\overline{E}_{Rz,Tool} = 0.0234°$. As $\overline{E}_{T,Sens}$ nearly reaches to the sensor accuracy, calibration results are assumed to be satisfactory. The end effector in robotic welding typically has to be positioned with an accuracy of around 2 $mm$ to achieve a satisfactory weld quality [10]. So the above results indicate a sufficient accuracy of the sensor and tool calibration for performing welding experiments.

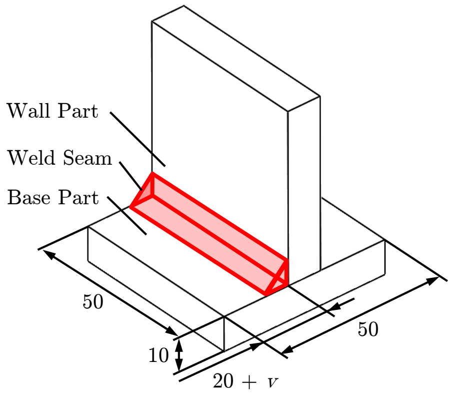


**Figure 6** Welding assembly consisting of base and wall part with identical dimensions and assembly variation $v$.

**Table 1** Welding process parameters for experimental validation.

| Welding parameter | Value |
|---|---|
| Voltage | 35 $V$ |
| Ampere | 180 $A$ |
| Wire Speed | 4.7 $m/min$ |
| Welding Speed | 4.5 $mm/s$ |
| Position of torch | $\alpha = 45°, \beta = 0°$ |
| Stick-out | 12 $mm$ |
| Filler material | Steel, $d = 1.2\ mm$ |
| Shielding gas | 10 % $CO_2 + AR$ |

# 5 Experimental Validation

The robotic welding system shown in **Figure 1** is used for experimental validation of the proposed approach. The 6-axis industrial robot is equipped with a 3D stereo camera to measure the geometry of the welding assembly. The 3D camera provides point cloud data with 360.000 points per measurement with a measurement point distance of around 0.2 $mm$ at an operating distance of $280 - 460\ mm$. As the approach is based on sensor measurement before execution of the manufacturing process, the sensor is not needed during the welding process.

An automatic tool changer is used to put the sensor end effector before execution of the welding process, as the 3D camera is not designed for usage in welding process conditions. For execution of the welding process, a welding end effector is attached to the robot flange. It consists of a typical welding gun for metal active gas (MAG) welding with a contact pipe diameter of 1.2 $mm$.

Experiments are performed on a test workpiece of non-alloy steel S355JR consisting of two identical parts to be joined by a fillet weld seam, shown in **Figure 6**. The parts are manufactured with tight dimensional tolerances of $\pm$ 0.05 $mm$ to minimize geometric errors between CAD models and real geometry of the single parts. The parts are preassembled by manual tack welding with defined assem-

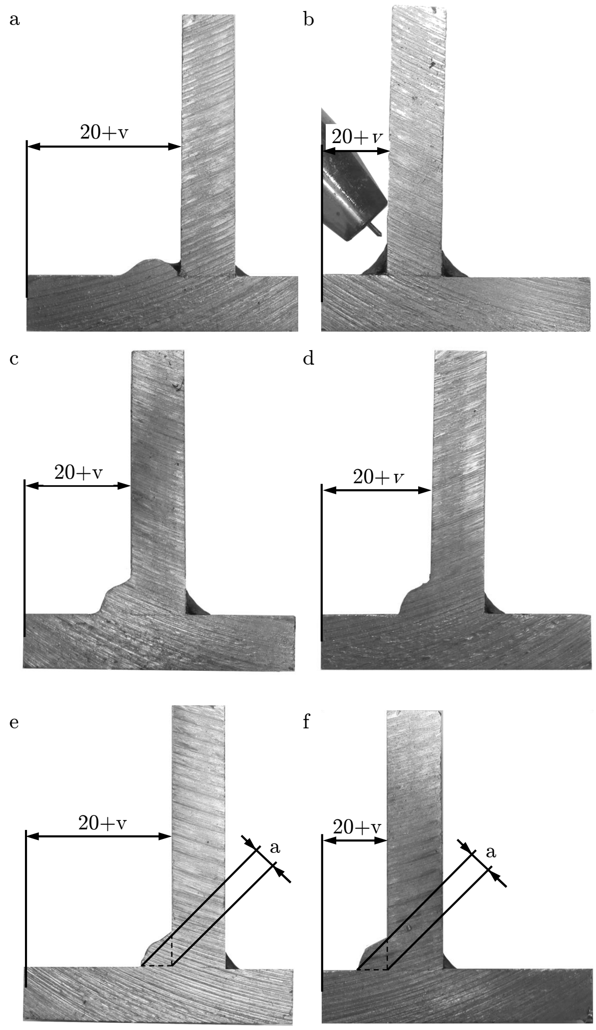


**Figure 7** Experimental results of welding process without assembly variation detection for (a) $v = +8$ *mm*, (b) $v = -8$ *mm*, (c) $v = 0$ *mm* and with assembly variation detection for (d) $v = 0$ *mm*, (e) $v = +8$ *mm*, (f) $v = -8$ *mm* and throat thickness $a$.

bly variations before execution of the robotic seam welding process. Therefore, an assembly variation parameter $v$ is introduced that affects the relative part positioning in one translational direction and enables testing for different assembly variation situations.

A MAG welding process is performed on test workpieces with different values of the assembly variation parameter $v$. The experiments are performed with and without usage of the proposed approach. The parameters of the welding process are shown in **Table 1**.

After welding, the test workpieces are sawed through perpendicular to the seam direction. This enables evaluation of the seam cross section area and thus determination of the throat thickness parameter $a$ of the fillet weld according to ISO 5817. **Figure 7** examplarily shows the results for $v = -8$ *mm*, $v = 0$ *mm* and $v = +8$ *mm*. Without variation detection, a variation of $v = -8$ *mm* results in a colli-

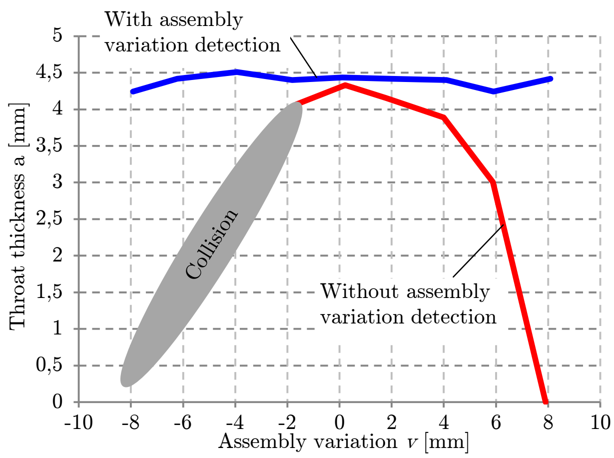


**Figure 8** Experimental results of weld seam throat thickness $a$ for different assembly variations $v$ with variation detection (blue) and without variation detection (red).

sion between welding gun and workpiece, so that no weld seam can be produced. For a variation $v = +8$ *mm*, the weld seam positioning is not sufficient to produce a seam that connects the two parts and no throat thickness $a$ can be measured. Only in the case with zero variation $v = 0$ *mm*, a correct seam quality can be produced. However, using the proposed approach shows satisfactory weld quality with a constant throat thickness $a$ for $v = -8$ *mm*, $v = 0$ *mm* and $v = -8$ *mm*.

The relationship between assembly variation $v$ and the resulting throat thickness $a$ for all experiments is shown in **Figure 8**. Experimental results without using the proposed approach show a decreasing throat thickness for a variation greater than zero $v > 0$ and less than zero $v < 0$. For $v < -2$ *mm*, a collision between welding gun an the workpiece geometry occurs with the used setup, so that no weld seam can be produced. For a variation greater than zero $v > 0$ *mm*, the throat thickness $a$ decreases exponentially up to $a = 0$ *mm* at $v = 8$ *mm* for which no joining of the two parts can be realized. Only in the case without assembly variations with $v = 0$ *mm*, the desired throat thickness of $a = 4.4$ *mm* can be reached.

Using the proposed approach however results in a constant seam quality for all experiments performed with a throat thickness of $a \approx 4.4$ *mm*. The approach hence improves the weld seam quality in the occurrence of assembly variations. Even for welding processes, like MAG-welding, where assembly variations can be tolerated to some extend, using the proposed approach enables to perform the welding process with optimum parameters.

# 6 Conclusions

In this paper, an approach has been proposed for detection of assembly variations to adapt the programming of a robotic welding system. Typical assembly variations, i.e. induced by manual preparation during tack welding were detected and used for automatic program adaptation.

The approach is based on 3D sensor measurements and the workpiece CAD model and allows for detection of assembly variations without the need to measure the joint geometry itself. This facilitates the sensor usage in SME productions and allows to detect assembly variations also on complex workpiece geometries, where the joint geometry cannot be measured with classical 2D seam tracking sensors. As the performance of the approach depends on a precise calibration of sensor and welding tool, a method for robust and accurate calibration is presented. Welding workpieces have been localized with an average translational accuracy of around 0.15 *mm*. The calibration of the welding tool showed a translational accuracy result of around 0.26 *mm*.

Experimental validation of the proposed approach was performed by a robotic MAG welding process on test workpieces of non-alloy steel with different assembly variations. It shows a constant weld seam quality and the practicality of the proposed approach in industrial applications. Assembly variations have been detected up to a translational variation of $\pm 8$ *mm*. Compared to a welding process without assembly variation detection, the proposed approach shows an increased weld seam quality. For high variations the robot welding programs without usage of the presented approach even lead to collision between workpiece and welding gun or to incorrect weld seam positions.

Future work will focus on more complex workpiece geometries and specific strategies for adaptation of the welding process.

# 7 Aknowledgement

The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement No. 287787, project SMErobotics.

Furthermore, the authors want to thank Mr. Konstantin Ksensow for support in implementation and testing of the calibration procedure.

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