Workpiece localization methods for robotic welding – a review

M.Sc. Gesine Schleth[a,b], Dipl.-Ing. Alexander Kuss[a], and Dr.-Ing. Werner Kraus[a]
[a]Fraunhofer Institute for Manufacturing Engineering and Automation (IPA), Stuttgart, Germany
[b]gesine.schleth@ipa.fraunhofer.de, +49 711 970-1047

Abstract

Frequent manual reprogramming of robots is one of the impediments for the installation of robotic welding cells in small and medium-sized enterprises (SMEs). CAD-based offline programming solutions yield potential to reduce these efforts. A central component of these automatic programming approaches is the localization of the workpiece's actual position in the robotic welding cell. This paper presents an extensive literature review on workpiece location for robotic welding as well as latest technological developments gathered at an international trade fair on welding. Comparing the approaches developed for robotic welding with those for other robotic applications such as bin picking, potential improvements are identified. It is reasoned that localization algorithms using offline training and global optimization will increase the flexibility of existing solutions if they are used as feature-based coarse localization independent of any prior knowledge of a workpiece's pose. This lowers the obstacles for SMEs to invest in robotic welding as it holds the potential to reduce setup times in a small lot size production environment.
Keywords: robotic welding, 6D object pose estimation, workpiece localization, machine vision

1 Introduction

Welding is one of the most common application areas for industrial robots. In 2016, 26% of worldwide operational stock were used for welding applications [1]. However, the installation of robotic welding cells (see **Figure 1**) in small and medium-sized enterprises (SMEs) is often precluded by their small lot sizes and high product variance that require frequent reprogramming. Reasons for reprogramming are manifold, e.g. welding assemblies deviating from their nominal geometry due to manual tack welding or reduced precision of fixtures by wear [2][3]. A manual adaptation of welding robot programs reduces the efficiency of a welding cell, so automatic solutions are indispensable.
The core problem of automatic adaptation of robot programs is to precisely measure the position and orientation of the workpiece or its weld seams. Measuring methods for weld seam detection involve laser line scanners mounted on the robot following the weld seam's expected trajectory. On the other hand, measuring the whole workpiece's location (and only implicitly that of its seams) has the advantage of being weld seam geometry independent and thus more applicable to high product variability scenarios. This paper focuses on the latter problem and aims to give an overview of current methods for workpiece localization to infer necessary developments improving their technology readiness level. It is structured as follows:
Section 2 defines the problem of workpiece localization. A classification of sensor systems and algorithms is made in Section 3.1, followed by introduction to other robotic application areas facing a similar problem in Section 3.2. A literature review in Section 3.3 presents current approaches pursued in research. These results are then compared with the industrially applied workpiece localization methods in Section 3.4 to deduct possible directions of future research in Section 4. Section 5 summarizes the findings.

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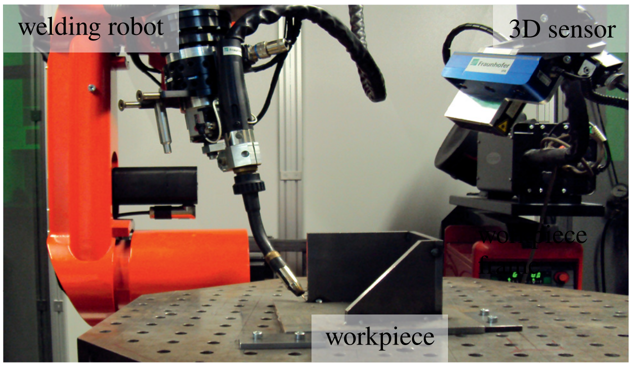
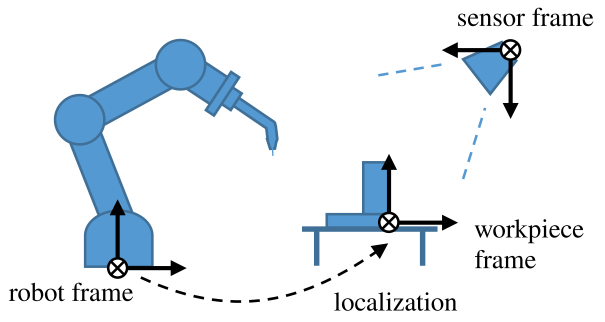


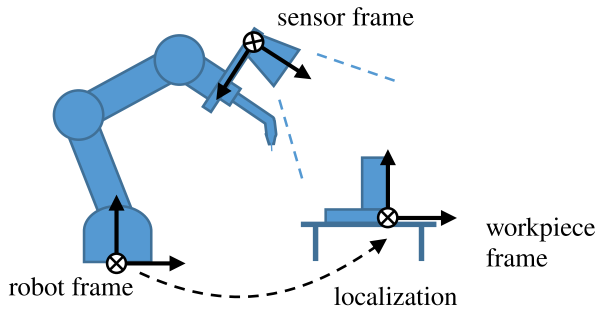
Figure 1 Robotic welding cell with sensor system for workpiece localization

2 Problem description

The problem of localizing a workpiece in a robotic welding cell can be defined as the determination of a workpiece's coordinate frame in relation to the robot world frame [4]. The result is a rigid body transformation containing infor-



(a)



(b)

Figure 2 Workpiece localization for robotic welding with sensor system mounted externally (a) and on the robot end effector (b)

mation on the position and orientation of the workpiece – its 6D pose in world coordinates. This pose is obtained by a calibrated sensor system whose measurements are evaluated using an algorithm that has specific knowledge of the nominal workpiece, for example its computer-aided design (CAD) model. **Figure 2** sketches the different coordinate frames in a robotic welding cell with an integrated sensor system in different mounting configurations.
The generalized process of workpiece localization is visualized in **Figure 3**. A measurement is obtained from the workpiece from which descriptive features are extracted. The next step compares them to the model workpiece's features in a matching routine. The workpiece pose is computed from the transformation aligning model and measurement features.

3 Workpiece localization methods

To contextualize the overview of current research on workpiece localization methods, a classification of existing approaches is given. Other areas in robotics facing the workpiece localization problem are presented. An analysis of research literature for welding and other robotic applications is presented, followed by an overview of current commercial solutions.

3.1 Classification

Detached from their application area, methods for workpiece localization can be distinguished according to the measuring principle of their sensor system, the extracted

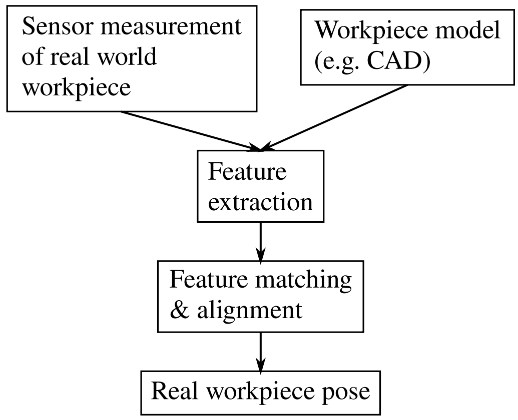


Figure 3 Workpiece localization process (adapted from [4, p. 17])

features, and the algorithms computing the localization information (refer to tasks in Figure 3).
Measuring or data acquisition principles are divided into contact and non-contact methods as shown in **Figure 4**. For example, the first are mechanical touch-trigger probes as used on coordinate measurement machines (CMMs) or the welding torch gas nozzle which gives an electrical signal when forming contact with the workpiece. Regarding non-contact measuring principles, optical methods are the most diverse [5][6]. Prevalent measuring principles generating depth information are triangulation using laser scanners and Time-of-Flight (ToF) sensors using the time-delay between laser ray emission and reflection. A third category is image analysis using monocular or stereo camera images [7]. Data acquisition methods can be classified not only according to the measuring principle, but also the density of the generated data. Tactile methods and laser point scanners measure individual points while most optical methods generate a dense depth information, also called 3D point cloud.
Features are individual measurable properties of a data set that are designed to be informative and non-redundant. Extracted features from measurements and reference models depend on the density of the available data and are generally adapted to the matching algorithm which is why an exhaustive list will not be given in the scope of this paper. They can roughly be classified as high- or low-level features depending on the complexity of the extraction step necessary to obtain them from the raw measurement data [4]. For example, the individual 3D points of a measurement can be used directly to match them to a reference model. In this case, the points can be considered low-level features. Surface normals generated from the surrounding points or oriented point pairs are another example for features needing simple extraction routines [8][9]. High-level features are e.g. geometric primitives, features derived from 2D vision such as 3D Harris corners [10][11][12]. Most features in 2D vision are appearance-based, meaning they are dependent on image intensities and color textures, reducing their application to an industrial environment with textureless and reflective workpieces [10].

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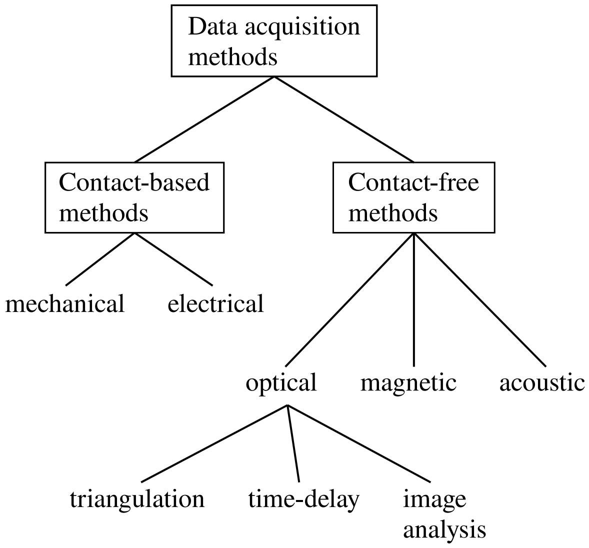

Figure 4 Classification of localization methods (adapted from [5, p. 405])

When focusing on 3D features, the localization problem is reduced to finding the rigid transformation between the features of a reference model (e.g. a CAD model) and a 3D measurement of the workpiece. This process is called feature matching or registration. Corresponding algorithms depend on the assumptions that are made of the measured scene: If the approximate pose of the workpiece and the view field of the sensor are known, algorithms using local optimization are suitable. A widely used method is the Iterative Closest Point (ICP) algorithm that minimizes the spatial distance between point features of model and measurement [13][14]. However, if there is knowledge about neither the workpiece pose nor where it is located in the sensor view field, a global optimization strategy is needed [15]. For this class of localization algorithms that assumes no prior knowledge of the workpiece's pose, a variety of strategies exist, e.g. methods involving clustering and search trees [4]. The latter may need an initial training phase or a database of pose templates that is generated offline.

3.2 Different application areas of workpiece localization

Abstracting the task at hand from the robotic welding application, other fields of research approaching workpiece localization such as bin picking and computerized numerical control (CNC) machining become apparent:
In fully automated feeding systems, unordered objects are picked up by a robot gripper from a container. In this application called "bin picking", knowledge of the objects' poses is required to be able to generate robot gripping motions. This is obtained by optical scans of the container that are evaluated by recognition and localization algorithms. Other applications with similar requirements are robotic "pick and place" where parts are localized on a conveyor belt and manipulated by a robot, and CNC machining cells. A fourth application area other than welding that could be seen as to employ workpiece location is object detection and retrieval in service robotics. However, the highly textured nature of every-day objects as well as the recognition problem that needs to be solved prior to the object localization makes the approaches used for this application wholly different to those in industrial settings [10].

3.3 State of research

Depending on the application area, approaches using different algorithms and features are popular in research publications which is why they are analyzed separately in this section. All approaches are summarized in **Table 1**.
Methods developed specifically for robotic welding use 3D point data acquired with tactile probes or optical 3D sensors that are mounted on the robot end effector or, less often, on a static fixture [16][17]. It is generally assumed that an approximate workpiece pose is known, reason being that the fixtures used in welding constrain the workpiece pose. The developed localization algorithms aim at compensating for small deviations between different workpieces of one batch, which is why the local minimization of an error metric is sufficient. The error metric represents the distance between the 3D measurement of the workpiece and its reference model, e.g. a CAD-model, for example the point-to-point distance of corresponding 3D points in measurement and reference. The features aligned in the minimization are either 3D points or other low-level features like lines or surfaces. A good initial pose guess and low-level features make ICP the prevalent matching and alignment algorithm [16][18][19].
In CNC machining, tactile probes are traditionally used as the workpiece geometry is usually simplified and a high accuracy is needed [20][21]. However, similar methods to those used for welding applications start to emerge, making use of the greater flexibility and data density of 3D optical sensors [22].
Contrary to welding, bin picking applications of workpiece localization cannot be said to have converged to the use of a single approach. Regarding sensor technology, monocular and stereo camera imaging as well as 3D depth sensors are used [23][24][25]. They are mounted statically over the object bin. Tactile probes or other sensors generating sparse data are unsuitable as measuring a bin containing several objects would be too time-costly. The measurement covering a number of objects is also the reason for the widespread use of high-level features that are only computed for a subset of key points of a measurement: Matching a smaller number of highly descriptive features reduces the computation time of matching and aligning algorithms. This is of importance as in bin picking several workpieces need to be discerned to be able to choose one that is easily accessible for a robot gripper.
To tackle the lack of an initial pose guess in bin picking, localization algorithms with global optimization routines are used. Clustering pose candidates from matching features and selecting the highest mode in cluster space is a frequent approach [10][26][27]. Voting-schemes determine

how pairs of matching model and measurement features cast votes for a workpiece pose, e.g. by using decision trees [23][25][28]. Another approach is to randomly chose matching feature pairs to compute a workpiece pose and to iterate until a distance threshold between model and measurement features is met.

For the presented approaches, a database of different reference poses is needed. A discrete set of possible workpiece poses is defined, from each of which features are extracted. These can be used directly as references for voting-schemes or for training a decision tree. The accuracy of the resulting workpiece pose is limited by the resolution of this database. Using the result of the global optimization as an initial guess, fine localization can be performed using local optimization [10][26][29][30].

Reviewing the approaches to workpiece localization in research, the absence of matching algorithms operating on a global scope in welding and CNC application becomes apparent (see Table 1). The reason for this contrast to bin picking applications is the assumption on the availability of a good initial guess for the workpiece pose.

3.4 State of industrial applications

Information on currently available workpiece localization methods for robotic welding was obtained during interviews with robot system suppliers at the international welding trade fair “Joining, Cutting, Surfacing” in Essen, Germany 2017. Suppliers provide referencing systems where the workpiece pose is computed from a small number of 3D points. Measurement devices are laser point sensors, or contact methods such as welding torch gas nozzles or wire tips. Tactile probes protruding from the welding table are rare, supposedly due to their inflexibility. One third of all interviewed suppliers uses laser line scanners to recognize joint start and end points. An equal share provides monocular camera solutions making use of geometrical workpiece features like lines or ovals and QR-codes to recognize their position and orientation.

4 Necessary developments

While research on workpiece localization concentrates on processing dense 3D data, stereo or depth sensors generating dense data find little use in industrial applications. This is unsatisfactory as it makes commercial localization methods insufficiently flexible for high product variance use-cases as in SMEs: Robot measuring programs for contact measurement need to be adapted for each new workpiece as seam detection algorithms do for each new type of welding seam. These methods also assume knowledge of the approximate pose of the workpiece. Commercial solutions using monocular cameras are scarcely more flexible as they rely on accurately positioned markers (QR-codes) or geometric features restricting their use to workpieces containing easily distinguishable geometrical characteristics.

To make 3D vision more attractive for welding applications, stereo and depth cameras need to be more robust to the hazardous welding environment. The trade-off between attainable accuracy and field of view of the sensors has to be softened so that large workpieces can be measured accurately.

Another reason for the lack of depth imagery in welding applications is the lacking robustness of present algorithms that presume a good initial guess of the workpiece pose. This greatly reduces the use-cases of workpiece localization for SMEs that are facing small lot sizes where initial setup times determine the productivity of a robotic welding cell. Limiting the deviation of the workpiece pose to justify the initial guess assumption also implies that costly fixtures constraining the workpiece sufficiently are necessary. This further decreases the productivity of robotic welding cells in high product variance scenarios.

To overcome these limitations of current commercial applications, research on workpiece localization algorithms for welding should focus on a greater robustness towards the initial pose guess. As shown in Section 3.3, research on

	Data acquisition method			Feature complexity		Localization algorithm scope	
Application area	Tactile probe	Depth sensor	Monocular/ Stereo	Low	High	Local	Global
Welding	[17][31]	[16][18][19][32][33][34]	–	[16][17][18][19][31][32][33][34]	–	[16][17][18][19][31][32][33][34]	–
CNC machining	[20][21][35][36]	[22][35][36]	–	[20][21]	[22][35][36]	[20][21][22][35][36]	–
Bin picking	–	[10][23][25][26][27][30][37][38]	[24][28][39][29][37]	[25][26][27][38]	[10][23][30][24][28][39][29][37]	[38]	[10][23][25][26][27][30][24][28][39][37]

Table 1 Classification of research applications of workpiece localization according to application area.

workpiece localization for welding relies on local matching algorithms dependent on a good initial guess. Improvements could be gained by adapting approaches used in bin picking scenarios, e.g. a voting-scheme using a pose template database. This could prove to be a good coarse initialization leading to faster and more accurate results of an ensuing fine localization. Another open problem in current research on workpiece localization for welding is the automatic definition of the measurement pose of a robot-mounted sensor. This is relevant in cases where the field of view (FoV) of the used sensor only partially covers the workpiece. Considering the negative correlation between the measuring accuracy and the size of a 3D sensor's FoV, as well as the large dimensions of welding workpieces, this is a likely scenario. In current approaches the sensor is positioned manually using expert knowledge to optimize the informative value of the workpiece segment within view. Automatic approaches need to take into account the amount of descriptive workpiece features in the FoV as well as the robot reachability and its pose dependent accuracy.

5 Conclusion

Comparing workpiece localization methods from different fields in robotics with solutions implemented in industry, it becomes apparent that current research approaches lower their chances in commercialization as they do not provide a greater flexibility than available systems. Assuming knowledge of the approximate pose of the workpiece, methods using local localization algorithms can compensate workpiece pose deviations to a small extent. Integrating approaches as developed for robotic bin picking using global localization algorithms should provide a greater flexibility in localization systems using dense 3D data in robotic welding. Another aspect is the automatic sensor view planning for robot-mounted 3D sensors reducing necessary expert knowledge in robot programming. These developments lead to more flexible localization systems lowering the obstacles for SMEs to invest in robotic welding.

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