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A generic data structure for the specific domain of robotic arc welding

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Abstract

The systematic analysis of robotic arc welding processes requires unified structured data, which is currently not available due to the diversity of data sources. This paper proposes an integrated data structure for the specific domain of robotic gas metal arc welding. The presented data structure contains a description of the welding system, the design of the welded parts, welding instructions, and time series of measured process data. Collected data enriched with semantic context is stored and analyzed using this data structure. The usefulness is exemplified but not limited by a use-case suggesting welding process parameters to the worker.
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1. Introduction

Robotic gas metal arc welding is a widely used bonding technique in manufacturing processes. Due to its complexity, the configuration and setup of a robot cell (see Fig. 1) still requires humans with expert knowledge to adapt the parameters to achieve the required quality of the welding seam. An approach to make the required process knowledge available in a computerized and digital form is using data mining techniques on welding data. Generating knowledge about the welding process by using data mining techniques requires a large and complete data basis of welding data. The term large in this context means that the data basis consists of multiple robot cells of different types and welding equipment. The term complete means that all information about the setup and configuration of the robot cell, which would be required to reproduce the welding seam, is included in the data basis. For an automated evaluation, the data base has to be structured, self describing and standardized. This means analysis algorithms can access a standardized data structure without the need of individual adaption to vendor specific formats.

Robot arc welding cells consist of different devices (see section 3.1), at least a robot and a welding power supply. Furthermore, these devices are provided by a number of different manufacturers and can be found in a large amount of combinations and configurations in different robot cells. If communication interfaces to those devices for reading data are available, they are implemented using a large variety of different data formats. Thus, automatic analysis is not applicable without further preparation of the data. Recently, the preparation of the data is done for each use-case, but there is a lack of interchangeability, reusability and comparability with other use-cases.

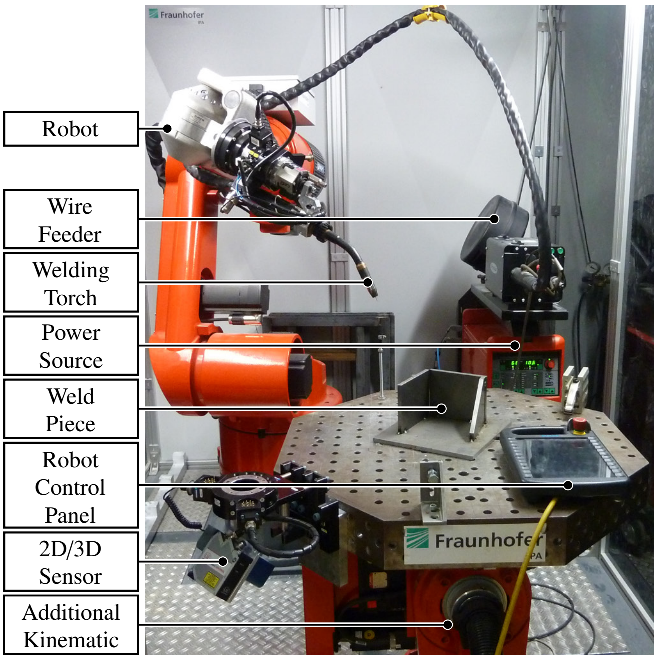

Fig. 1. Robot welding cell at Fraunhofer IPA.

With regards to data analysis based on large databases taking different configurations of robot welding cells into account

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Robot arc welding cells consist of different devices (see section 3.1), at least a robot and a welding power supply. Furthermore, these devices are provided by a number of different manufacturers and can be found in a large amount of combinations and configurations in different robot cells. If communication interfaces to those devices for reading data are available, they are implemented using a large variety of different data formats. One approach of storing this data is the so called data lake [1,2], where the raw and unstructured data is stored in one database. Using a data lake simplifies the process of storing data, because of the reduced data modeling and integration effort. However, it still requires structuring effort later on, when data analysis should be performed. Thus, automatic analysis is not applicable without further preparation of the data. Recently, the preparation of the data is done for each use-case, but there is a lack of interchangeability, reusability and comparability with other use-cases. With regards to data analysis based on large databases taking different configurations of robot welding cells into account the authors propose a generic data structure for the domain of robotic arc welding with a self describing semantic to store welding data.

This paper is structured as follows: In section 2, the state of the art is presented. The setup of a typical robot cell is explained and an overview of relevant data formats to describe a robot cell is given. In section 3, the approach for a novel generic data structure for the domain of robotic arc welding is presented. An exemplary implementation of a robot cell with the novel data structure is shown in section 4. Section 5 presents a use-case to demonstrate an automated evaluation of welding data to extract process knowledge.

2. State of the art

2.1. Data formats and semantic web technologies in robotics

Methods for information management stemming from IT and the semantic web have been used in automation and robotics for a while. Ontologies offer context to information and it is expected that the use of semantics will ease integration and increase autonomy of robotic systems. In the field of service robotics several ontologies have been developed [3–5]. This has sparked the development of a set of ontologies in robotics by IEEE [6,7].

The technical basis for the use of semantics in robotics typically stems from IT from the Semantic Web [8]. The Resource Description Format (RDF) [9] allows to represent information in triples and to model relations similar to human language using subject, verb and object. RDFS (Resource Description Framework Schema) [10] extends RDF with basic concepts for ontologies. The Web Ontology Language (OWL) [11] further extends the capabilities of RDFS and is very commonly used for the description of ontologies. Several subdialects, e.g. OWL DL and OWL lite, are available and impose additional restrictions to facilitate reasoning. The SPARQL protocol and RDF Query Language (SPARQL) [12] are the query languages of the semantic web that allows retrieval of structured information stored in RDF.

The Semantic Web technologies are used in several robotic applications from plant information processing [13,14], knowledge integration [15], robot programming [16] or CAD design [17]. However, Semantic Web technologies are not providing a generic and complete data structure for the domain of robotic arc welding.

AutomationML is a format for the description and exchange of plant engineering information. It is an open standard format (IEC 62424) based on XML [18]. AutomationML relies on different other open standards from the IT-world: Computer Aided Engineering Exchange (CAEX) is used to model the hierarchical structure of the plant. COLLAborative Design Activity (COLLADA) is used for geometry data and interactive 3D applications although it is easy to reference other geometry data formats. PLCopen XML is used for PLC programs and generally for storing logic information. The Standard for the Exchange of Product Model Data (STEP) offers similar features, e.g. mechanical design, electrical design, material and information on the machine structure.

A high level framework for process descriptions in different domains, e.g. manufacturing and business processes is offered by the Process Specification Language (PSL) [19]. PSL was developed to enable the exchange of process data between different software systems. It has a strong focus on enabling automatic reasoning on processes and for example allows the evaluation of process consistency and rule compliance.

Due to the importance of welding processes for the industry, extensive research led to multiple norms for various countries to standardize and classify welding processes. A welding procedure specification (WPS) specifies the necessary steps to achieve repeatable weld quality [20]. The norm EN ISO 15609 [21] describes a set of variables that are required for a specific application to assure repeatability. The American Welding Society, acting under ANSI rules for consensus standards, publishes a Standard Welding Procedure Specifications (SWPSs) [22].

The process variables of a welding process can be recorded as time series data. Bader et al. define in [23] a time series data base (TSDB) as a system that can (i) store a row of data that consists of timestamp, value, and optional tags, (ii) store multiple rows of time series data grouped together (e.g., in a time series), (iii) can query for rows of data, and (iv) can contain a timestamp or a time range in a query. Storing time series data in a TSDB compared to storing it in an XML file requires less disk space and brings faster read and write access. Therefore TSDB are well suited for storing welding process data.

2.2. Data mining techniques for welding data

Several data driven approaches for robotic welding applications exist to extract process knowledge from welding data. In [24] a decision tree algorithm is presented to predict weld geometry parameters based on welding process data. The dataset includes 3573 welding test cases with process data. In [25] a model tree trained on more than 3000 classified welds is used to predict the weld diameter. The data was collected with the same type of robot cell and identical equipment. In [26] the Mahalanobis distance method is used to predict the welding bead geometry based on the current and voltage waveforms. The data was collected by experiments with a single robot cell and a fixed set of welding equipment. In [27] statistical methods are used to extract knowledge patterns in order to suggest improvements for new product development. The data source is the ABB data center with a large collection of robot cycles from in-field robot cells. The authors point out that due to the versatile use of robots, finding a generic representation for the data is still a challenge.

2.3. Conclusion from the State of the Art

The given examples of data mining techniques (see section 2.2) in the domain of robotic welding show that it is possible to generate process knowledge from welding data [24–27]. For all examples a data set is required to develop algorithms and train models. The data is either collected for a specific use-case and is stored in a data structure that fits this use-case, or the data is manually converted to a target data structure to fit the target use-case. No generic data structure to store welding data is used to enable the exchange of data without the need of manually converting for each specific use-case.

AutomationML is capable of describing plant data. However, it is not designed to store time series of process data. Time Series Data Bases, like InfluxDB, are capable of storing time series data, but they are not well suited to store plant data. Document based databases like MongoDB are designed for storing documents, like CAD or PCD files, without the need of defining a scheme upfront. But to the best of the author's knowledge there exists no generic data structure for the domain of robotic arc welding with a self describing semantic to store welding data in a complete and reproducible way.

3. Approach

The novel approach of this paper is to define a generic data structure for the domain of robotic arc welding. The first design goal of this data structure is reproducibility for the welding seam, meaning that all information required to setup a robot cell (see section 3.1) and perform the same welding seam again is included. This goal is reached by keeping the data structure generic, so it is possible to add devices from different vendors with different data formats.

The second design goal is to use data formats which are already well established. The CAEX format of AutomationML (see section 3.2) is used to model a robot cell with a self describing semantic. However, using just AutomationML to store welding data of a robot cell will run into a scalability problem, which is described in section 3.3. Therefore, the proposed data structure stores the welding data in separate databases and integrates the meta data and access information of this data into AutomationML.

3.1. A typical robot cell

A typical industrial robot cell for welding (see Fig. 2) consists of a robot arm and welding equipment. A welding torch is mounted as a tool at the robot flange and supplied with welding wire by the wire feeder. A robot control unit commands the motion of the mechanical robot arm. The welding torch and the wire feeder are controlled by the welding power supply.

The robot control unit is running the robot program and is sending position setpoints to the drives via fieldbus with a cycle time of a few milliseconds. The robot control unit also sends process parameter settings to the power supply unit and commands the start and stop of the welding process. The current control loop of the welding process is closed inside the welding power supply.

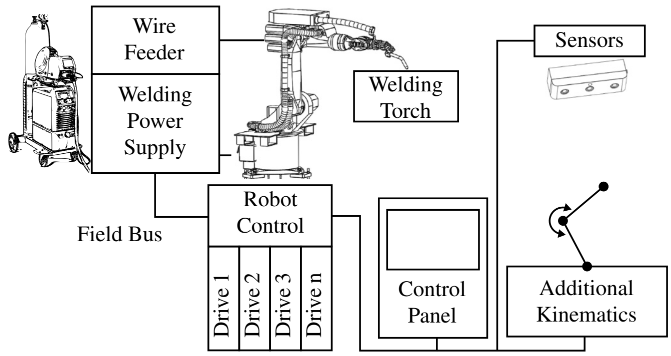

Fig. 2. Topology of a typical robot welding cell.

Table 1. List of sensors in a robot cell and their possible data format.

Sensor type	Purpose	Possible data format
3D Camera	3D stereo cameras are used to capture three dimensional pictures to measure e.g. the real geometry or position of the workpiece	*.pcd
2D Laser scanner	2D laser scanners can be used for quality tests of the welding seam e.g. to check the design throat thickness or to determine the angle between the welded parts	*.slk
Microphone, Piezoelectric sensor	The acoustic information can be used to analyse the welding process regarding process stability like in [28]	*.wav
Temperature sensor, Humidity sensor	With a temperature and humidity sensor it is possible to record environmental conditions during the welding process	*.csv

Besides the robot controller and the welding power supply, a robot welding cell can have additional sensors to measure the welding process. Those sensors can be vision sensors, accoustic sensors or environmental sensors measuring the temperature or the humidity. In table 1 an exemplary and incomplete list of sensors used in robot welding cells is given. Depending on the type of the sensor their data is stored in different data formats like point cloud data (PCD) for vision systems or comma separated values (CSV) for temperature and humidity sensors.

3.2. Generic data structure

The proposed data structure does contain (i) plant data, (ii) document data and (iii) cyclic data. Plant data contains all physical devices, their connections, their interfaces and topology. It also maps the available variables to the devices. Document data does contain all configuration files, firmware files or parameter setting files. Cyclic data are all time series variables that can be stored as a value/timestamp pair. This data structure is focused on welding process data for data mining techniques, therefore it does not contain ERP data, like part numbers, prices or customer names.

The modelling language AutomationML is well suited for describing a plant topology. In AutomationML, the semantics of an element can be defined using role classes. Two new role classes, *Document* and *TimeSeriesVariable* (TSV), are introduced. They have attributes like unit, data type and description to store the meta information of this element. A Document is for example a configuration file, which contains the parameter settings of a welding power supply or a robot controller. TimeSeriesVariable are for example trajectories of welding current and voltage or the welding torch position. The hierarchical structure of the CAEX format allows to add and map new time series variables or document elements to devices and then map devices to robot cells (see Fig. 3).

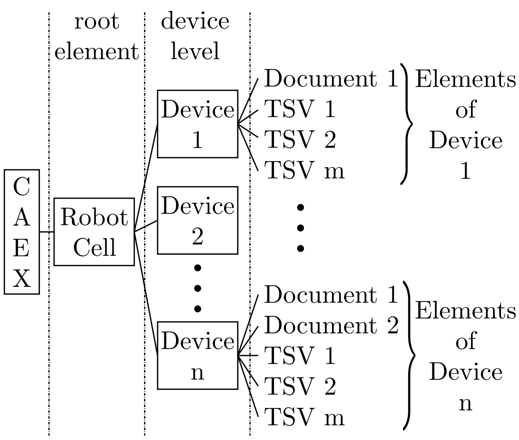

Fig. 3. Hierarchical structure of elements in a robot cell.

3.3. Scalability problem of single file solutions

AutomationML is capable of storing the topology information of the robot cell in a human readable form. In section 3.2, it is shown how elements with their meta information are added to the devices. Besides just adding the meta information, it would also be possible to add the time series or document data itself to the AutomationML file. This file would then contain all required information to run automated data mining techniques and could be used as exchange format between different parties. However, this single file approach has a scalability problem. With a growing file size, reading and writing operations will become slower. When the file size grows beyond the maximum storage of a single hard disk, the single file approach will fail.

An alternative approach is to use databases. Databases are optimized for efficient storage of large amounts of data. Distributed databases can also locate the data on multiple physical storage devices and therefore solve the scalability problem of the single file approach.

3.4. Integrating databases into AutomationML

Each type of data has different use-case characteristics and therefore different requirements for its data format in terms of human readability, frequency of read and write access, or the compression level. Thus, each type is stored in the data format and database that is best suited to meet the specific requirements. However, to enable the exchange of welding data between multiple parties, a common and standardized data format is required. Therefore, the authors propose a data structure which uses databases for storing data and integrates the meta information of this data into the CAEX format of AutomationML. A single AutomationML file can then be used to exchange the meta information of a robot cell, while the data itself is stored in separate databases.

To build data mining techniques on top of the CAEX format, a mechanism is required to receive the welding data from the databases. Therefore, the information on how to access a database and query the data of a specific variable is also stored as attributes in the CAEX format. Each element in the CAEX format receives a unique id. All data related to this element are tagged with this id. This structure allows an automatic evaluation of welding data of different robot cells, which are stored in different databases.

4. Exemplary implementation of the data format

An exemplary implementation using the proposed data format is realized by describing a complete robot cell. This robot cell consists of a Reis robot, a Fronius Welding Power Supply, a Wire Feeder and an Ensenso Camera for measuring the welding seam geometry. All documents are stored in the object database MongoDB and all time series variables are stored in the time series database InfluxDB. The robot cell is modelled in AutomationML by using the AutomationML Editor to represent the hierarchical structure of the plant in CAEX format (see Fig. 4). The AutomationML file is then stored as a document in the MongoDB. Each document has a timestamp and a unique id, so it is possible to track the change history of the AML file to see which elements have been added or removed.

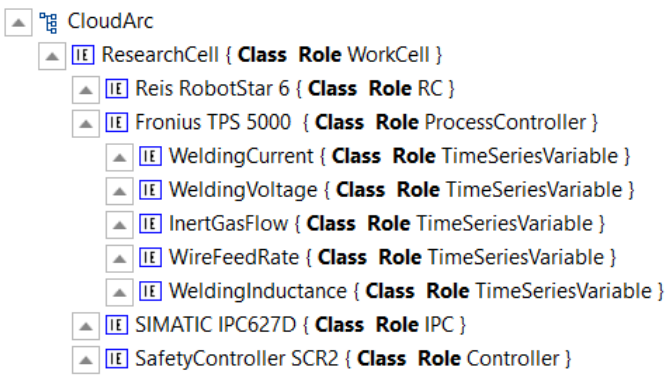

Fig. 4. Excerpt of the CAEX model in AutomationML Editor.

The time series variables are stored in an InfluxDB instance. Each variable is stored as a stream of timestamp and value pairs and is tagged with the unique id used in the CAEX model. In figure 5 the complete architecture is shown.

Other documents like CAD files for the welded part, welding procedure specifications or robot programs are also stored in the object database MongoDB. Each of those documents are tagged with a timestamp and their unique id, which are initially defined in the CAEX file.

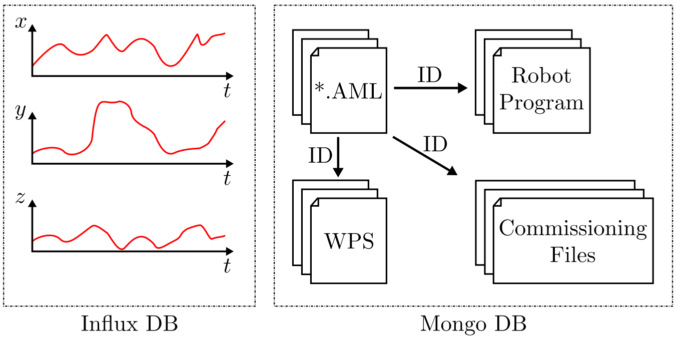

Fig. 5. Multiple database architecture with InfluxDB and MongoDB.

5. Use-Case

In this section an exemplary use-case for generating process knowledge by applying data mining techniques on welding data is presented. Most robot welding systems are still manually parameterized. The parameterization process has multiple degrees of freedom and requires expert knowledge. One degree of freedom is the velocity of the welding torch, which has a significant impact on the quality of the welding seam. The correct setpoint for the velocity depends among other variables on the type and thickness of the material and the type of seam. An experienced user of robot welding systems has implicit knowledge on how to set the welding velocity parameter for a specific set of boundary conditions.

By having a large set of welding data, it is possible to find often used and well tested velocity setpoints given a set of boundary conditions. The first step is to find welding datasets with similar boundary conditions (type and thickness of material, type of seam). With the proposed data format, it is possible to filter all datasets for boundary conditions. In figure 6 the velocity of the welding torch for multiple data samples is plottet with respect to the thickness of the material. The data samples are filtered for the type of seam and the material.

The second step is to analyse the welding data and draw conclusions for the quality of the welding seam. Assuming that an operator will change the parameterization until the resulting quality is satisfying, an exemplary algorithm for estimating the welding quality is based on the following steps:

(i) identify a welding order with a lot size greater than ten

(ii) identify the index i of the welding job, for which the welding parameters have last been modified

(iii) all parameterizations for welding job index smaller than i are considered to have bad quality, all parameterizations with a welding job index greater or equal i are considered to have good quality

The quality of the weld in figure 6 is indicated by the shape (filled circle: good quality; hollow circle: bad quality). This plot requires welding data samples of lots of different parts, with different material, thickness, velocity setpoints and type of seams. Since the presented data format is not yet adopted by the industry, such a large set of data samples does not yet exist, therefore the plot is created with dummy data to better illustrate how this use-case works. The required number of recorded welding seams for a meaningful evaluation of the use-case displayed in figure 6 can be extrapolated as follows. It is assumed that on average 10 welds of one type of material and thickness will generate 2 data points (one with bad quality and one with good quality). Choosing a thickness resolution of 0.1 mm in the range of 0 to 10 mm will result in 100 steps. For each step 10 data points will be required, which results in 50 welds and thus for 100 steps in 5 000 welds. Therefore, generating a map for 20 different types of seam increases the number of needed welds to 100 000.

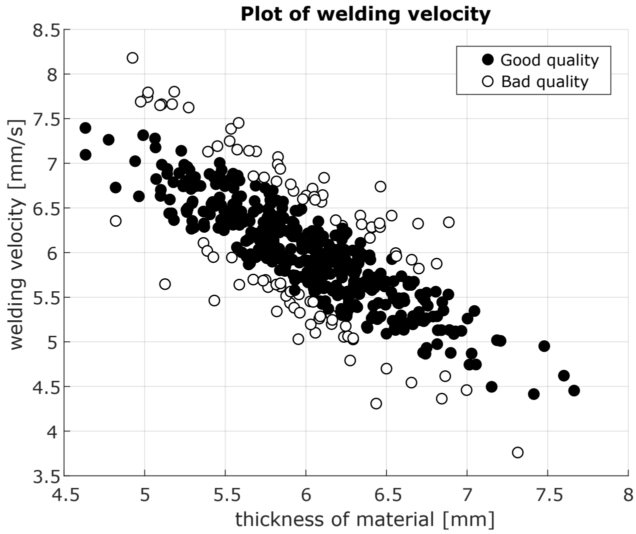

Fig. 6. Exemplary visualization of welding data samples (dummy data).

The third step is to analyse the velocity setpoints with data analysis methods like regression or cluster analysis. The primary goal is not to find optimal settings, but rather to reduce the degrees of freedom in the parameterization process. The operator of the welding robot system therefore no longer needs to decide which value for the welding velocity is used, instead he receives a suggested setpoint by the welding assistent system. This makes it possible for non-experts to use robot welding systems. However, the semantic modeling of welding data still requires an expert, which is a general limitation of semantic modelling.

This use-case takes only three input variables (type of material, thickness of material, type of seam) and produces one output variable (quality of seam). However, more use-cases are possible, taking the information provided by the robot program, design data, welding procedure or camera sensors into account. The presented data format can store all the required information and save the context of the data to enable more use-cases in the future. One example could be the automatic workpiece position presented by Diaz et. al. [29]. Having a large set of welding data available, would also allow to validate new algorithms without the need of running test series.

6. Conclusion and Future Work

In this paper, a novel data structure for the domain of robotic arc welding is proposed. The scalability problem of single file solutions is solved by storing the welding data in databases. The exchangeability of welding data is achieved by storing the meta data and access information to the databases in a defined semantics in the CAEX format of AutomationML. An exemplary implementation of the data structure for a complete robot welding cell was presented. The usefulness of having a complete set of welding data for data mining techniques was demonstrated by an exemplary use-case. Due to the diversity of manufacturer specific data formats, the data still needs to be converted before it can be stored in this generic data structure. Thus, individual expert knowledge and effort is required for creating the semantic model.

The exchange of welding data with mutual benefits between parties is still an unsolved problem. Currently, the users of robot welding systems lack incentives to collect and share their welding data or make it publicly available. An incentive could be to get access to the results of analytic services based on welding data. However, most data mining techniques require a large set of welding data to extract knowledge of the welding process, which is currently not available.

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