AUTOMATING A CAR PRODUCTION LINE ADJUSTMENTS BY USING CASE-BASED REASONING

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Abstract: As a test bed for the Case-Based Reasoning (CBR) approach for automating processes adjustments, the Volvo Car manufacturing process for parts known as crossmembers is chosen. To test the CBR based system, a subset of solved cases is selected and fed as simulated new cases, to developed prototype CBR system. The results show that the CBR is a valuable and promising methodology that can be used for improving this, and other similar industrial processes.

Keywords: Case-based reasoning, Car production, Process control

1 INTRODUCTION

High quality demands a production process which can adapt and react to intra-process variations. High quality also demands good control of production processes, for which often process models are used. If a production process is too complex to be modelled explicitly, it is advantageous to employ other tools (like case-based reasoning) which can contribute with decision support to the operator, or be applied directly to the process, provided that an adequate automation level is implemented.

In computer science Case-Based Reasoning (CBR) is a method for implementing an artificial intelligence algorithm that has the ability to identify a solution to a problem, using previously solved problems as guidance. Even though the CBR systems have successfully been implemented before for improving some industrial processes, it is still a new and promising approach that has not yet been widely tested for its usefulness.

CBR is a very promising methodology also for implementing quality assurance. It allows product measurements, and its related adjustments to the production line, to be stored as cases in a so called case library (database with problem-solution pairs). The CBR system can learn and produce suggestions to adjust production system, and manufacture a quality part, which should reduce time and effort in solving problems in manufacturing, and also reduce environmental impact by reducing resources and spill in manufacturing. The main strength lies in the fact that it enables directly reusing actual cases that have been solved in the past. The approach is especially suitable when simulation and modelling is to complex and adjustments cannot be calculated in real time. This is often the case in a real manufacturing environment where the relationship between the result and adjustment is so complex that it cannot be predicted; as too many factors influence the outcome. Even skilled technicians learn over time how to adjust in order to get the desired result. Technicians' experience may have been acquired through costly mistakes whereas their memory is not as precise as a computer memory. CBR enables harvesting this experience and also transferring it between experts and to less experienced operators.

Due to the inevitable variations in input parts' characteristics and fluctuations in manufacturing process parameters, it is often necessary to adapt controllable process variables to the imposed changes. The adjustments of an assembly process are usually done when it is detected that a produced part falls out of tolerances. It is usual in a car production line that the assembly process adjustments are done by experienced operators and engineers.

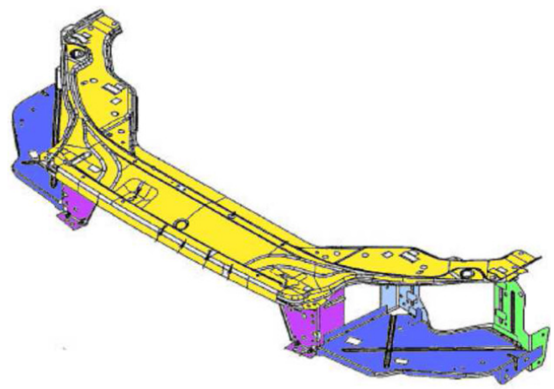

Fig. 1. Breakdown of crossmember pieces.

Nevertheless these interventions do not come without a price in potentially slower production rates and increased possibility for imperfections in the final product characteristics. Additionally, not all of the technicians are able to correctly adjust the manufacturing process. Since the adjustments made are based on previous experience, i.e. on previous corrective actions and their outcome, the CBR is imposed as a natural way of automating the adjustments. CBR provides adjustment actions based on the knowledge accumulated over time in a so-called case library, which is the counterpart of the knowledge accumulated by technicians.

As a test bed for the CBR based approach for automating process adjustments, the Volvo Car manufacturing process for parts known as crossmembers is chosen. A crossmember is a metal part that goes inside the frontal part of the car and serves as a support and for housing other parts. The CBR based system, collects the measurements of the finished parts geometry, together with the process adjustments done by the technicians, and builds the case library. By using the CBR the system is capable of suggesting corrective actions for cases in which a finished part falls out of tolerance, or even before a finished part falls out of tolerance.

2 CROSSMEMBER PRODUCTION LINE

The crossmember is formed by assembly of smaller pieces in a symmetrical way. The blue, purple, green and light blue pieces shown in Fig. 1 are placed in a dedicated workbench by a technician. The yellow piece is placed by an industrial robot once the technician's pieces are placed correctly on the workbench.

In order to manipulate positions of the ingoing parts, the workbench in which the pieces are placed has placement pins which can be slightly displaced by adjusting the tie in knots that holds them to the workbench. The workbench holds the pieces together so that industrial robots can take part in the manufacturing process, welding the pieces together. Adjustments are used to compensate for the variation of the ingoing parts in order to reach the specification demands on the final sub assembly, the crossmember.

Finished parts are measured on 290 predefined points by a Coordinate Measuring Machine (CMM). Each of these feature points have their associated tolerance levels predefined. If the measurement indicates that the part is out of specification, problems may arise when mounting the crossmember into a car or there may be other problems such as in lamp fixation and similar.

3 CASE-BASED REASONING

Case-Based Reasoning (CBR) is an artificial intelligence technique in which the system solves a problem basing its output on the experience collected from solving similar problems in the past, inspired by the doctrine that similar situations lead to similar outputs (Aamodt and Plaza, 1994). The focus of CBR systems is to have a case library with enough cases to encompass a considerable amount of problem-solution pairs, and therefore be able to solve all the problems that may arise on a predefined task.

The original work in CBR was performed by Schank and Abelson in 1977 (Schank and Abelson, 1977). In 1983 Janet Kolodner developed the first CBR system named Cyrus (Kolodner, 1993). Cyrus was an implementation of Schank's dynamic memory model and contained knowledge, as cases, about the travels and meetings of a former US secretary of state. Until about 1990 CBR was known only inside the research community. When Lockheed corporation began to use a CBR system named CLAVIER (Mark, 1989) for the baking of composite parts in an industrial oven, the CBR has become widely known technique which became more and more established in time. At present time it may be considered that case-based reasoning fits well for classifying new measurements or

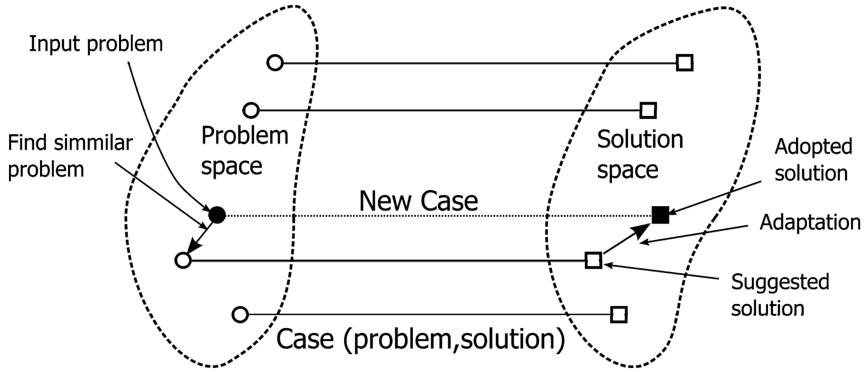

Fig. 2. Problem and solution space

sensor signals based on experiences of past categorizations (Xiong et al., 2012). The main strength lies in the fact that it enables directly reusing concrete examples in history and consequently eases the knowledge acquisition bottleneck (Olsson et al., 2013).

CBR systems are based on two simple assumptions. The first is that similar problems have similar solutions; therefore a system that wants to solve a new problem will be in a much better starting point if it has a solution from a similar problem already available. The second assumption is that similar problems tend to happen multiple times.

A CBR system maps a specific problem to a specific solution. If a new problem arises and a known solution is not known a priori, the CBR system proposes a solution based on the similarity that this new problem has to other problems that have been solved before. If the proposed solution proves to be efficient, the solution is then stored in the case library and the system has successfully learned to solve a new problem. The CBR system has following main stages for solving a problem that has been issued (Aamodt and Plaza, 1994):

- Find the nearest problem,
- Retrieve the solution for the most similar problem from the case library,
- Reuse the information from said solution adjusting it as necessary (possibly by a pre coded algorithm),
- Revise or check the proposed solution,
- Retain the solution for future use if proved successful.

In classical CBR theory, there are two spaces defined for a CBR system (see Fig. 2): the “problem space” and the “solution space” (Richter and Weber, 2013). Since the system needs to compute a solution according to similar experiences, a mathematical approach to detect the most similar (or nearest) case in the problem space has to be implemented.

3.1 CBR Knowledge Model.

CBR is a knowledge-based system. Knowledge-based systems are a sub-class of intelligent systems that are designed by having a knowledge base in an independent module. Knowledge can either be represented explicitly or be hidden in an algorithm. In any case the knowledge is presented in some formulation. The formulation is stored in a so called knowledge container. There are four main knowledge containers in CBR:

- **The vocabulary container** - determines what one can discuss explicitly, i.e. by which terms the system being explored can be described with. There are generally an infinite number of terms that can describe a certain object, but only a few are relevant for a specific task.
- **The similarity container** - consists of all knowledge needed to determine what makes a case similar to another. There are multiple ways to calculate similarity: the use of simple similarities where the values are either equal or not, the use of weights to represent relative importance of the attributes, the use of fuzzy algorithms that consider all attributes and their importance at once.
- **The case base container (case library)** - contains stored cases. The cases can be collected from the past, generated, or be artificial (these are usually used for testing purposes). This is the main knowledge contained in CBR.
- **The Adaptation Container** – the most important knowledge in adaption container are the rules on how to adapt cases stored in the case library to a new case. In other words, the adaptation container contains information on how to modify a solution.

In the following chapter specifics will be presented of the knowledge containers used for the CBR system applied to crossmember production.

4 CASE-BASED REASONING APPLIED TO CROSSMEMBER PRODUCTION

4.1 The knowledge model of the prototype CBR system

The vocabulary container main elements for CBR applied to crossmember production are:

- Pin – an adjustable point in fixture holding the crossmember input parts,
- Pin direction – Pin can be adjusted in one or more possible Cartesian space directions (X, Y, Z),
- Feature – measurable geometrical characteristic of an assembled part,
- Feature direction – feature can be measured in one or more Cartesian space directions (X, Y, Z), or normal (perpendicular) to the assembled part surface (usually denoted with NOR).
- Tolerances – each feature has a tolerance interval defined for each direction. If a measured value for a feature in a certain direction falls out of tolerance interval, that generally means that an adjustment is needed to correct the process.

By the term "current case" it is meant a new measurement for a finished part containing at least one feature whose measured value falls out of tolerance interval. Additionally, a case is defined as ‘‘unfinished’’ if it lacks information about adjustments and/or outcome measurements, and it is defined as ‘‘finished’’ if it includes all the parts (the precise parts are defined below).

The case base container, the heart of the CBR system, is consisted of the stored finished cases each represented by:

- measurement of an assembled part that had at least one feature measurement out of its associated tolerance interval,
- adjustment,
- measurement after adjustment.

The nearest case retrieval is done by calculating distances between the current measurement (problem case) and the cases stored in the case library. This can be done by using various similarity measures (Richter and Weber, 2013). For the prototype system root mean square distance (RMSD) is used. Given a new problem case A, the distance to a target case T is calculated as shown in the following equation:

$$Dist_{A,T} = \sqrt{\frac{\sum_{k=1}^{n}(T_k - A_k)^2}{n}}\,, \tag{1}$$

where k is a k-th feature in a certain direction and n is the total number of measured features in all their associated directions. Additionally, the normalized root-mean-square deviation distance (NRMSD) has been used. It is the RMSD divided by the range of measurement values. RMSD and NRMSD form the similarity container for our CBR system prototype.

By using the similarity container the prototype CBR system compares the current problem case (measurement of an assembled part with at least one feature being out of its tolerance level) to the measurements before adjustment, for all the cases stored in the case base container. The system then presents the nearest cases and more importantly their adjustments to a user (technician) in an adequate and user-friendly way. The technician then decides which one of the presented adjustments to apply, or forms a combination of the presented adjustments. Consequently our prototype CBR system does not have an algorithmic adaptation container but the user is the one doing the adaption of the presented potential solutions.

4.2 CBR crossmember production prototype system software architecture

A prototype system that leverages the CBR for crossmember production has been developed involving a web interface, a server and a case library. The primary goal of the system is to aid technicians to adjust production equipment according to geometric product measurements. The prototype is able to import production data and store in a database accessible from a web interface.

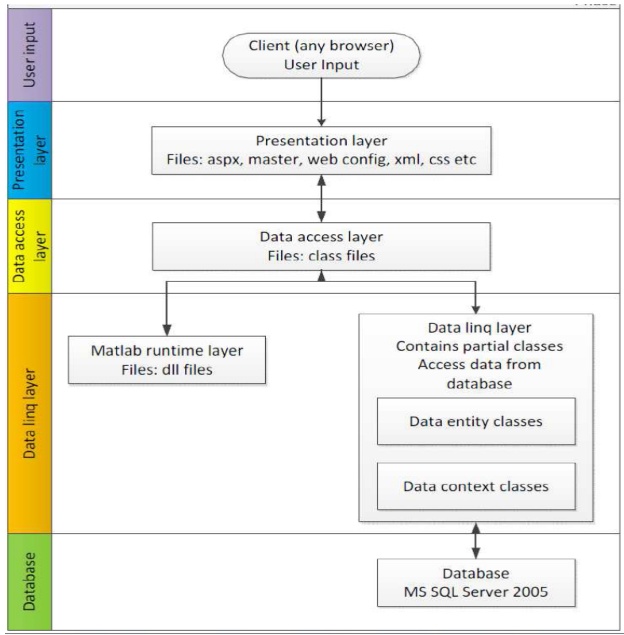

Fig. 3. System architecture.

The prototype system for using the CBR in crossmember production consists of different layers which, by modularizing different functions, make the software easier to test, maintain, and analyse. The overall architecture can be seen in Fig. 3.

The data link layer is comprised of data entity classes and data context classes which communicate with the SQL Server Database and the data access layer. The data access layer communicates with the database with the help of data link layer. The presentation layer communicates with the data access layer to get data from either MATLAB scripts, or the SQL Server. The layered design of the system, together with modularizing the different functions, makes the software easier to evaluate.

The heart of the system is the SQL Server relation database management system which hosts the case base container. In addition to containing tables for hosting the case base container, the database has a number of additional tables needed by the other part of the software system (e.g. table containing users of the system).

The system's most common use case is depicted in Fig. 4. A user can upload a measurement, enter adjustments in the adjustment log and finally upload the outcome measurement (measurement after adjustment). The server is responsible for finding the nearest cases for the current case, send the adjustments to the user, and to store and maintain the cases.

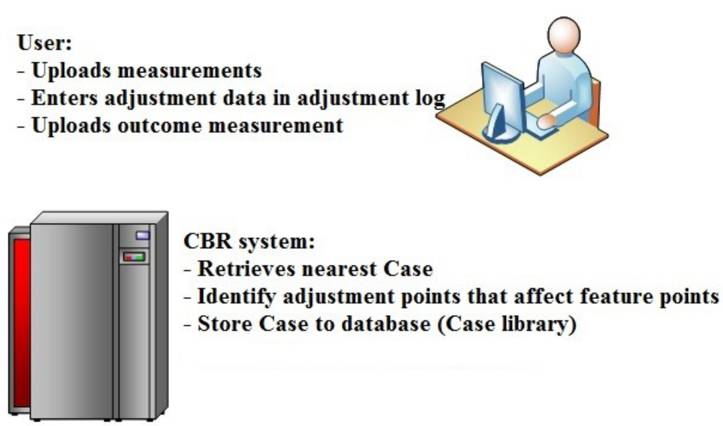

Fig. 4. System use case

The system retrieves the nearest case using data from the uploaded measurement and displays it to the user. The system also finds out which adjustment points affects the selected feature points and presents them to the user. When the initial measurement and outcome measurement are uploaded and the adjustment data is entered the case is considering finalized and the system saves it to the database.

5 TESTING THE PROTOTYPE CBR SYSTEM

To test the CBR based system a subset of solved cases is selected and fed to the CBR system. These cases are used to simulate "current cases" (see section 3.1). The solved cases come with the technicians' adjustments that successfully corrected the process. These adjustments are compared to the ones suggested by the CBR system. Note that for the testing purposes the cases selected are complete so that their adjustments can be compared to the system suggested adjustments. In the operational scenario only problem cases (without known adjustments) will be presented to the system.

The precise testing procedure is as follows:

1. Fourteen cases are chosen randomly from the CBR case library containing in total 127 cases.
2. For each of the fourteen cases:
   a. The current case is excluded from the CBR case library,
   b. The adjustment done for the current case is extracted and stored,
   c. Similarity is calculated between the current case and all the other cases in the database,
   d. The cases are sorted by the calculated similarity,
   e. Adjustment for the most similar case is extracted and stored ,
   f. The current case is returned to the CBR case library so that it can be compared to the other cases,
3. The known adjustments (step b) are aligned to the adjustments done in the most similar cases (step d) and exported (saved).

This procedure results with a table comparing the done adjustments with the suggested adjustments (Table 1).It can be noticed in Table 1 that there are five cases (out of fourteen) for which the suggested adjustments are not on the same pins, and/or directions, as the adjustments done. Still the similarity between each of these four cases and their suggested cases are all higher than 85%. Even though this result may be unexpected, or seem incorrect, it is quite possible that the suggested adjustments are suitable for these cases, as they can be better than the expected ones, i.e. the ones that were done by technicians.

Table 1 Comparison between the adjustments done and the suggested adjustments.*

Case num.	Known adjustment				Adjustment for the most similar case				Similarity between current and the most similar case	
	Pin	Direc-tion	Initial shim	Change in shim	Pin	Direc-tion	Initial shim	Change in shim	RMSD	NRMSD (%)
1	19	X	6.8	-1.5	19	X	7.4	-2.1	0.31	91.15
2	19	X	4.2	1.3	19	X	4.6	0.9	0.17	95.03
3	22	X	3.8	1.2	22	X	3.4	1.6	0.14	94.65
4	**25**	X	6.8	-0.8	**22**	X	3.4	1.6	0.26	90.87
5	**25**	X	4.6	1.4	**19**	X	6	-0.5	0.08	85.88
6	25	**Y**	3.2	1	25	**X**	5.6	0.4	0.06	97.50
7	27	X	4.2	-0.4	27	X	3	0.8	0.12	95.27
8	**27**	**X**	3.4	0.4	**39**	**Z**	5.2	0.4	0.10	95.80
9	27	Y	4.8	-0.8	27	Y	3.6	0.4	0.23	92.47
10	27	Y	3.2	0.8	27	Y	2.8	1.2	0.46	90.22
11	**37**	**Z**	4.8	1.4	**25**	**X**	6.4	-0.4	0.13	95.28
12	37	Z	3.4	1.4	37	Z	2.8	2	0.22	96.18
13	39	Z	6.8	-1.4	39	Z	6	-0.4	0.08	97.17
14	39	Z	4.2	1.4	39	Z	3.6	2	0.15	95.36

*The shaded rows indicate the cases in which the suggested adjustment pins and/or directions are not the same as in the done adjustments (the Pin names and/or directions that differ are bolded).

In all the other cases the pins and their associated directions coincide in the suggested adjustments and the adjustments done. The comparison between the changes in shim values show that in general the suggested shim changes are quite close to the changes done. As the number of the stored cases will increase (in the production system) it can be expected that this precision in the suggestions will increase as well.

In the presented test only the most similar cases (to the current case) have been used. In the envisaged operation system the technician will be presented with a number of the most similar cases (e.g. five) together with their adjustments, from which he can choose or adopt them for the current case.

6 CONCLUSION

A prototype CBR system for crossmember production has been presented together with the results of testing its usefulness and precision. The presented results of the testing show that CBR performs very well, especially if one considers that the case base database that the system is currently equipped with is quite small. It contains only 127 cases. In a production environment as the number of the stores cases will grow, the usefulness of the CBR system is expected also to grow since its knowledge base will be bigger. The results support the conclusion that CBR is a valuable and promising methodology that can be used for improving this, and other similar manufacturing processes.

The testing procedure presented takes into account only the most similar cases. In real life situations technician will be presented with a number of the similar cases, and select one of the adjustments, or adapt and produce a new adjustment, which is potentially better than the adjustment for the most similar case. The new adjustment is stored in the database as a part of a new case and the system has gained experience, and improved its overall performance (learning).

Evidently our prototype CBR system does not have an algorithmic adaptation knowledge container: the user is the one doing the adaption of the presented potential solutions. In addition to providing new knowledge to the system the adjustments done by using the CBR are stored and will be used as a source to develop algorithmic adjustments in the future work on the corossmember production CBR system. We also plan to do additional testing of the CBR system by introducing additional new measurements, possibly obtained by in-line measuring system.

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