RESISTANCE SPOT WELDING PROCESS IDENTIFICATION AND INITIALIZATION BASED ON SELF-ORGANIZING MAPS

Heli Junno, Perttu Laurinen, Eija Haapalainen, Lauri Tuovinen, Juha Röning
ISG, Department of Electrical and Information Engineering,PO BOX 4500, 90014 University of Oulu, Finland

Dietmar Zettel, Daniel Sampaio, Norbert Link, Michael Peschl
Fachhochschule Karlsruhe, Institut für Innovation und Transfer, Moltkestr. 30, 76133 Karlsruhe, Germany

Keywords: Resistance spot welding, Self-organizing maps, Process identification, Initialization parameters

Abstract: Resistance spot welding is used to join two or more metal objects together, and the technique is in widespread use in, for example, the automotive and electrical industries. This paper discusses both the identification of different spot welding processes and the process initialization parameters leading to high-quality welding joints. In this research, self-organizing maps (SOMs) were used, and optimal features for the training parameters were sought. According to the results, processes can be classified by specific features. When introducing new data to trained SOMs, the welding operator can visually identify similar processes. After process identification, the most similar process is retrieved and a self-organizing map is trained for this specific process. The initialization parameters leading to successful welds in that process can thus be identified, which means that the manufacturers can use them to initialize their welding machines.

1 INTRODUCTION

Spot welding is used to join metal objects. It is widely used, for example, more than 100 million spots are produced daily in the European vehicle industry (TWI). This study explains how SOMs have been used to identify processes and to find the initialization parameters leading to good results.

In this paper, the aim is to compare the characteristics of a sample measured from a new process to information gathered from existing processes, to find a similar process and then to apply the process parameters leading to high quality joints. With this approach, the set-up time of new processes can be significantly reduced.

The research in the field has concentrated on estimating the quality of welding by using neural networks and regression analysis. The studies have utilized different features extracted from data. In many studies the variation of resistance over time has been used. Neural network and regression models have been generated based on the dynamic resistance pattern by, for example, (Aravinthan, 2001) and (Cho, 2002). Studies using other variables include approaches involving neural networks with tip force, the number of weld cycles, the weld current and the upslope current (Ivezic, 1999).

In this paper, the term 'process' is used differently compared to the previous studies on process control of spot welding. In our study, the welding machines, the material and the thickness of the material can vary in different processes, but the changes in current, electrode force or electrode wear are thought to be internal to the process. In other studies the term 'process' has been used to refer to the internal changes, including differences in electrode wear (Mintz, 1995). In other application areas, such as the copper flash smelting process, SOMs are used in process control but in these studies, too, the emphasis has been on the internal variations of processes (Vermasvuori, 2002).

2 DATA DESCRIPTION AND PRE-PROCESSING

The data used in this study comprise measurements of welding tests done at Stanzbiegetechnik (SBT). The data set contained 5 test series (1107 welding

Junno H., Laurinen P., Haapalainen E., Tuovinen L., Röning J., Zettel D., Sampaio D., Link N. and Peschl M. (2004).
RESISTANCE SPOT WELDING PROCESS IDENTIFICATION AND INITIALIZATION BASED ON SELF-ORGANIZING MAPS.
In *Proceedings of the First International Conference on Informatics in Control, Automation and Robotics*, pages 296-299
DOI: 10.5220/0001128802960299

a) b) c) d)

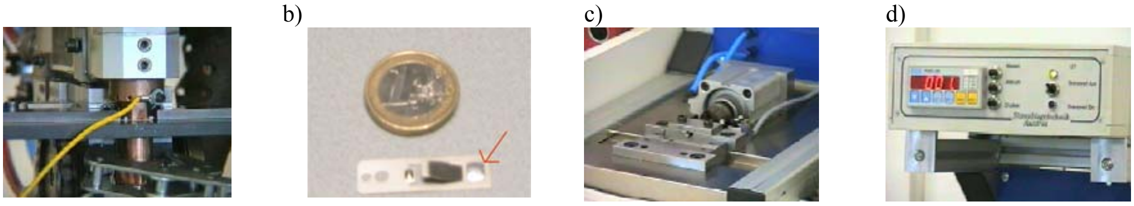

Figure 1: a) metal objects are joined using resistance spot welding, b) the welded part, c) the welding joint is torn apart in a destructive test by a quality assurance device, d) tensile strength is shown on the screen of the quality assurance device.

experiments). The materials can be seen in Table 1. The experiments were done by welding two metal objects together and after that tearing the objects apart in a destructive test (Figure 1). Each of the observations contains measurements of current and voltage signals recorded during and the tensile strength of the spot measured after the welding.

The resistance curve, derived from the voltage and current signals, contains the necessary information for comparing the processes. Since it was not feasible to train a SOM with all the data points of a signal curve, suitable features were extracted. Every resistance signal was divided into ten parts of equal length, and their averages were chosen as features. However, the whole feature set was not used, but the number of features was reduced to avoid cross-correlation and to eliminate overlap. Furthermore, the data were divided into training and test data sets, which consisted of 80 and 20 percent of the data, respectively.

In this work, the quality criterion was given as tensile strength, and the distribution of quality varied. For example, the quality limit for SBT 1 was 160 N, while for SBT 3 it was 550N.

Table 1: The materials used

Test series	Base material	Contact material
SBT 1, SBT 2	0.18mm Stainless steel	Silver nickel 0.5x0.9mm^2
SBT 3, SBT 4 (Time variation)	0.18mm Nickel-Beryllium Stainless steel	Silver nickel 0.5x0.9mm^2
SBT 5	0.18mm Nickel-Beryllium	Silver nickel 0.7x1.5x2.3mm^3

3 METHOD

The self-organizing map is a method that visualizes high-dimensional data in a two-dimensional space. This is done by keeping the topologic and metric relations of the two-dimensional space as close as possible to the relations of the initial space.

The SOM is usually formed of neurons on a regular low-dimensional grid. The neurons are model vectors $\mathbf{m}_i=[m_{i1}, m_{i2}, \dots , m_{in}]$, where n is the dimension of the input space. The training is done iteratively by choosing a data sample $\mathbf{x}$ and finding the closest model vector $\mathbf{m}_c$ (best-matching unit).

When the best-matching unit is found, it and its closest neighbors are updated with the equation

$$\mathbf{m}_i(t+1) = \mathbf{m}_i(t) + \alpha(t)h_{ci}(t)(\mathbf{x}(t) - \mathbf{m}_i(t)),$$

where $\alpha(t)$ is the learning rate factor and $h_{ci}(t)$ is the neighborhood kernel centered on the winner unit c. In this study, the SOM Toolbox, a function package for Matlab implementing the Self-Organizing Map algorithm, was used (HUT). For more information on SOMs, (Kohonen) is recommended.

4 RESULTS

The study was divided into two phases: process identification and search for initialization parameters. The features selected were generally the same in both cases, but the effect of welding time was ignored when searching for the initialization parameters, because it was the same inside process.

A strategy for deploying the results is presented in Figure 2 and a case study of the implementation is presented in the following chapters.

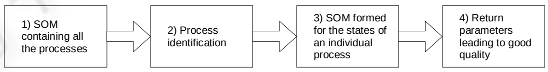

Figure 2: Steps for deploying the results.

4.1 Process identification

Figure 3a) shows a trained SOM. The division into 5 regions can be seen from the U-matrix. Now, the division given by the SOM is researched in more detail, because it is not yet certain that the different regions in the map contain information from different processes.

In Figure 3b), the spots of the 5 test series are labeled with the numbers 1-5. These labels are assigned to the map elements representing the curves belonging to the corresponding cluster. From Figure 3b), it can be seen that all the regions visible in the U-matrix contain only different processes. However, the division in the lower part of the map only points out the differences inside the processes 1 and 2, which are thought to be similar processes and it is therefore not considered as an important division.

The identification of different processes with this

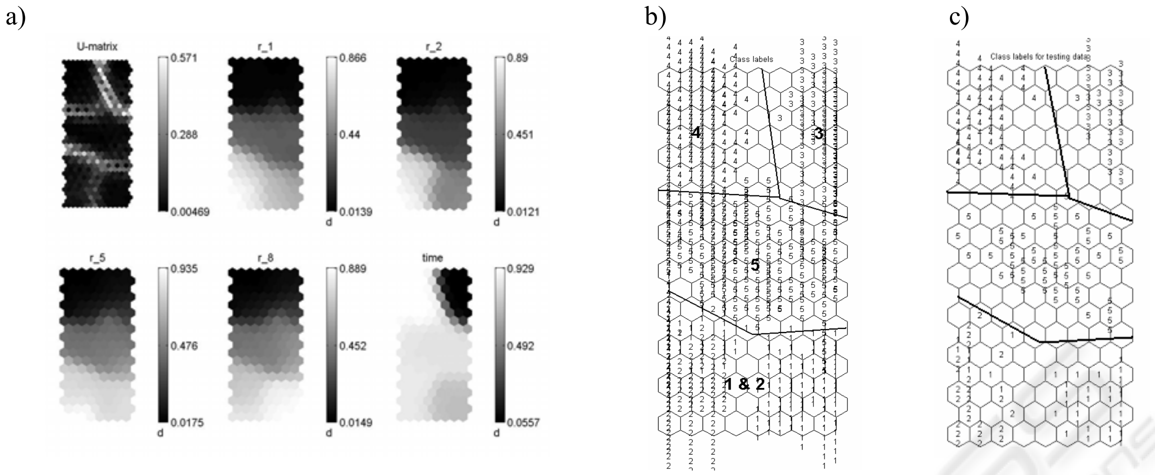

Figure 3: a) The SOM for all the test series from SBT when the means with the least cross-correlations of ten equally long parts and welding time were used as features. The following abbreviation is used: r = resistance. The numbers 1,…,10 refer to the means of the respective tenths of the signal. b) The labels for the map shown in a). c) The labels for the testing set.

method seems to be straightforward, but to be more confident, the test set can be introduced into the map. The Figure 3c) shows the corresponding labels. All the welding experiments of the test set are located in the correct regions. This allows the operator to identify manually the most similar process from a database of existing processes on the basis of welding experiments conducted on the process of the user.

4.2 Search for initialization parameters

After identifying the most similar process, the search for the suitable initialization parameters for that particular process can be started. In this paper, the results for process number 3 are presented in greater detail. The actual SOM trained with the data from the SBT process number 3 is not shown, but Figure 4 shows the labels related to the map. In the Figure 4a) the quality values of the welding spots shown as labeled, b) and c) the pre-set values used by the welding machine.

A welding spot is classified as successful if its tensile strength is more than 550N. From Figure 4a) it can be seen that, in the middle right part of the map, all the welds are of high quality. The low quality welds are shown as grey areas, while the high-quality welds are shown as white. The area that consists only high-quality welds is marked by a black line[1]. The figures b) and c) show that the parameters of the welding machine in that area are: current=3.7 and force=15.8. In fact, all the spots welded by a combination of those values are there[2].

With this knowledge, it can be assumed that the correct parameters to be used with the welding machine are the current value of 3.7 and the force value of 15.8. These assumptions can be tested with the test data. In Figure 4d), the tensile strengths for the testing data are shown labeled. For every weld from the testing set, the best-matching unit from SOM is identified, and the corresponding tensile strength is used as a label. Because in Figure 4d), the successful tests are located inside the successful area that was formed in the training phase, the parameters can be considered good enough. Therefore, the parameters can be delivered to the manufacturer, who can use them to initialize his welding machines.

5 CONCLUSIONS

The study was divided into two different phases: process identification and search for initialization parameters. According to the results, the different processes could be identified on the basis of the features extracted from the signal curves. Also, processes close to each other could be differentiated. Furthermore, after identifying the most similar process, the initialization parameters leading to high-quality welds could be found inside that process.

The authors will continue to explore the usage of more extensive data sets and to address in more detail the questions that arose during the study. Answers will be sought to the following questions: Can the method of setting up the welding parameters be automated? Can the initialization parameters be

[1]There is one node in the upper right part of the successful area with one unsuccessful test, but a closer analysis shows it to have been formed when the force had a value of 14.8.

[2]There is also another region where the current value of 3.7 and the force value of 15.8 co-occur. However, in that

region the welding help parameter, which does not show in the maps, was not applied.

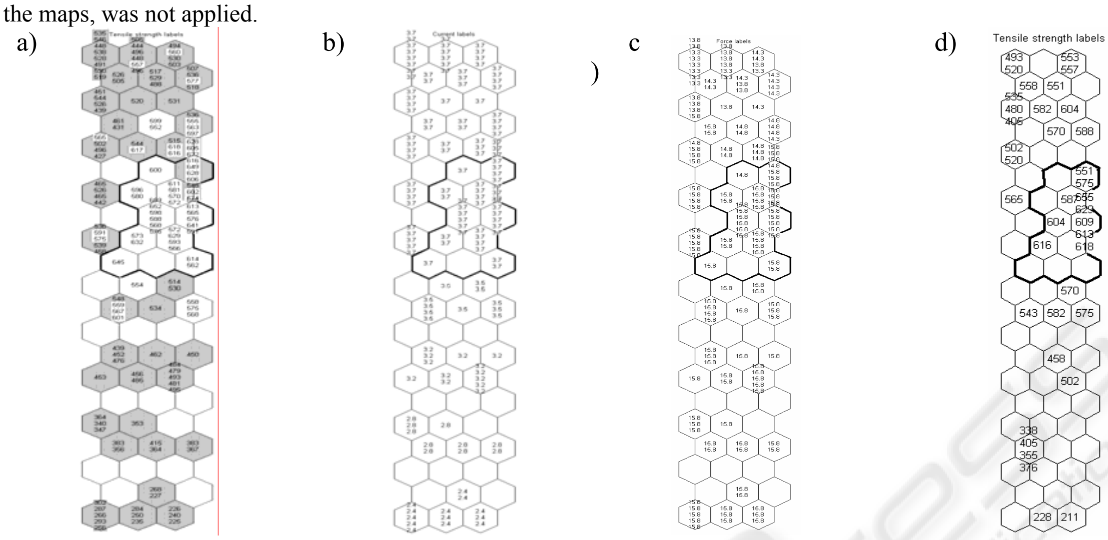

Figure 4: The labels for the map trained for SBT3, a) tensile strength, b) pre-set current values, c) pre-set force values. d) Tensile strength labels for the testing set.

delivered to the manufacturer if there are also unsuccessful welds in the successful area? And is it possible to differentiate between processes without taking the effect of time into account?

ACKNOWLEDGEMENTS

We would like to express our gratitude to our colleagues at Fachochschule Karlsruhe, Institut für Innovation und Transfer, in Stanzbiegetechnik, in Harms + Wende GmbH & Co.KG and in Technax for providing the data set and the expertise needed at the different steps of the research project. Furthermore, this study has been carried out with financial support from the Commission of the European Communities, specific RTD programme “Competitive and Sustainable Growth”, G1ST-CT-2002-50245, “SIOUX” (Intelligent System for Dynamic Online Quality Control of Spot Welding Processes for Cross(X)-Sectoral Applications”). It does not necessarily reflect the views of the Commission and in no way anticipates the Commission’s future policy in this area.

REFERENCES

Aravinthan, A., Sivayoganathan, K., Al-Dabass, D., Balendran, V., 2001. A neural network system for spot weld strength prediction, *UKSIM2001, Conf. Proc. of the UK Simulation Society*, Pages: 156-160.

Cho, Y., Rhee, S., 2002. Primary Circuit Dynamic Resistance Monitoring and its Application on Quality Estimation during Resistance Spot Welding, *Welding Researcher*, Pages 104-111.

Fachochschule Karlsruhe, http://www.fh-karlsruhe.de/, the homepage of the university, referenced 10.2.2004.

Harms+Wende, Web site of Harms&Wende http://www.harms-wende.de/. Referenced: 10.2.2004.

HUT, Helsinki University of Technology, http://www.cis.hut.fi/projects/somtoolbox/, referenced 10.2.2004.

Ivezic, N., Alien, J. D., Jr., Zacharia, T., 1999. Neural network-based resistance spot welding control and quality prediction, *Intelligent Processing and Manufacturing of Materials, IPMM '99. Proceedings of the Second International Conference on*, Pages: 989 –994.

Kohonen, T., 1997. *Self-organizing maps*, Springer-Verlag, 2nd edition.

Mintz, D., Wen, J.T., 1995. Process monitoring and control for robotic resistive welding, *Proceedings of the 4th IEEE Conference on Control Applications*, Pages: 1126 –1127

Stanzbiegetechnik, SBT, http://www.stanzbiegetechnik.at, referenced 10.2.2004.

Technax, http://www.technaxindustrie.com/, referenced 10.2.2004.

TWI World Centre for Materials Joining Technology, information available at their homepage: http://www.twi.co.uk/j32k/protected/band_3/kssaw001.html, referenced 10.2.2004.

Vermasvuori, M., Enden, P., Haavisto, S., Jamsa-Jounela, S.-L., 2002. The use of Kohonen self-organizing maps in process monitoring, *Proceedings of IEEE International Symposium Intelligent Systems*, Pages: 2- 7 vol.3.