

Studying the Quality of Resistance Spot Welding Joints Using Self-Organising Maps

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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. The quality of the welding joint is estimated by destructive or non-destructive tests. In this work, a method was developed that can be used to study the quality of a welding spot without destroying the joint. In this paper, the quality of the welding spot is analysed by using the diameter as a measure of quality. The relations between the diameter of the welding spot and certain features extracted from the welding signal curves are studied by dividing the signal curves into ten parts of equal length and using their averages as training parameters. Self-organising maps are also trained by using the most dissimilar features of the feature set. The relations between the diameter and the other features can be easily seen from the respective maps. According to the results, compression force has a notable influence on the size of the diameter. Two general rules of spot welding were confirmed by our study, which indicates that large values of diameter co-occur with small values of compression force and vice versa. Also, small values of current and small values of some features of voltage correlate with small values of diameter. This dependency naturally only holds true within reasonable limits of maximum current (to prevent splashing) and minimum force. The results also show that the quality of the welding spots can be inferred from data on other welds.

Keywords: resistance spot welding, self-organising maps, quality assurance.

a)

b)

c)

Introduction

Resistance spot welding is used to join metal objects. It is widely used in, for example, the electrical and automotive industries, where more than 100 million spot welding joints are produced daily in the European vehicle industry only [TWI]. The quality of welding spots is controlled by destructive or non-destructive methods. In destructive testing, the joint is torn apart, and the diameter of the welding spot is measured. An example of non-destructive methods is ultrasonic testing, where a high-frequency wave is transmitted into the joint, and the quality of the welding spot is interpreted based on the reflections of this wave. This kind of a test, however, needs specially trained staff, and the welding spots to be controlled must be checked in a special testing facility. Also, there is no suitable online quality assurance system on the market.

This study explains how self-organising maps have been used to interpret the quality of welding spots. The method is based on the interpretation of data available from welding experiments. In this study, only standard measuring equipment was used, but compression force meters may not be available for all welding machines. Therefore, in the future studies, compression force will not be used, because the aim is to develop a quality control method that will not require any extra equipment.

The relations between the quality of the welding spot and certain features extracted from the signal curves measured during the welding were studied for a set of 192 observations with quality reference data from destructive



Figure 1: a) metal objects are joined using resistance spot welding, b) the welding joint is torn apart in a destructive test, c) quality is estimated from the diameter of the welding joint.

testing. After determination of the relationship between the quality parameters and the signal curves by using this data set, the results can be applied to new welds of similar process type, and their quality can be estimated from the signal curves. This will reduce the cost of destructive testing and eliminate the need for hardware-oriented quality control methods.

The research on computational quality assessment techniques in the field has concentrated on estimating the quality of welding by using neural networks, regression analysis and mathematical methods. The studies have utilised different features extracted from data. The variation of resistance over time (dynamic resistance pattern) has been an important explanatory variable in many of the studies. Artificial neural network and regression models have been generated based on the dynamic resistance pattern by, for example, [Aravithan] and [Cho]. Cho compared regression analysis with neural networks, which demonstrated the superior accuracy of the neural network estimator. Unfortunately, the sample consisted of only 60 measurements, and the leave-one-out method was used to measure the estimator performance, which limits the significance of the conclusions. Studies using other input variables include approaches involving neural networks with tip force, the number of weld cycles, the weld current and the upslope current [Ivezic].

All the methods used so far produce an abstract mapping function between the feature profiles and the quality measures optimised to reflect the corresponding relation of the sample data set. In contrast, SOMs perform clustering of feature patterns, where similar patterns form a cluster characterised by a representative pattern. The clusters are presented as a two-dimensional map, with the map location distances reflecting the similarity of the clusters. The map arrangement allows direct interpretation and understanding of the interrelations

between the features and their relations with the quality of geometric considerations.

Data description and pre-processing

The data used in this study comprise measurements from welding tests done at Voest-Alpine Transport Montage Systeme GmbH, Austria. The data set contains observations from 192 experiments where two metal sheets were welded together using a resistance spot welding machine, (Figure 1 a)). The sheets were then torn apart in a destructive test (Figure 1 b)), and the quality of the welding spot was defined based on the diameter of the welding spot (Figure 1 c)).

Each of the observation sets contains measurements of current, compression force and voltage signals recorded during the welding and the size of the diameter measured after the welding. The signals were measured at intervals of 0.04 milliseconds.

Each of the current, compression force and voltage signals is composed of about 7000 values. It is not reasonable to train a self-organising map with so many data points - rather, suitable features must be extracted from the signal curves. In this study, every signal was divided into ten parts of equal length, and their means were chosen as features. This is shown in Figure 2, where the original data points have been connected to a polygon with black lines, while the white curve plateaus represent the means.

In this work, the quality criterion is given as the diameter of the welding spot, which must exceed 4 mm to represent a good joint. It is important to develop methods for discriminating between these low-quality joints and good ones. A histogram of welding spot diameters is shown in Figure 2.

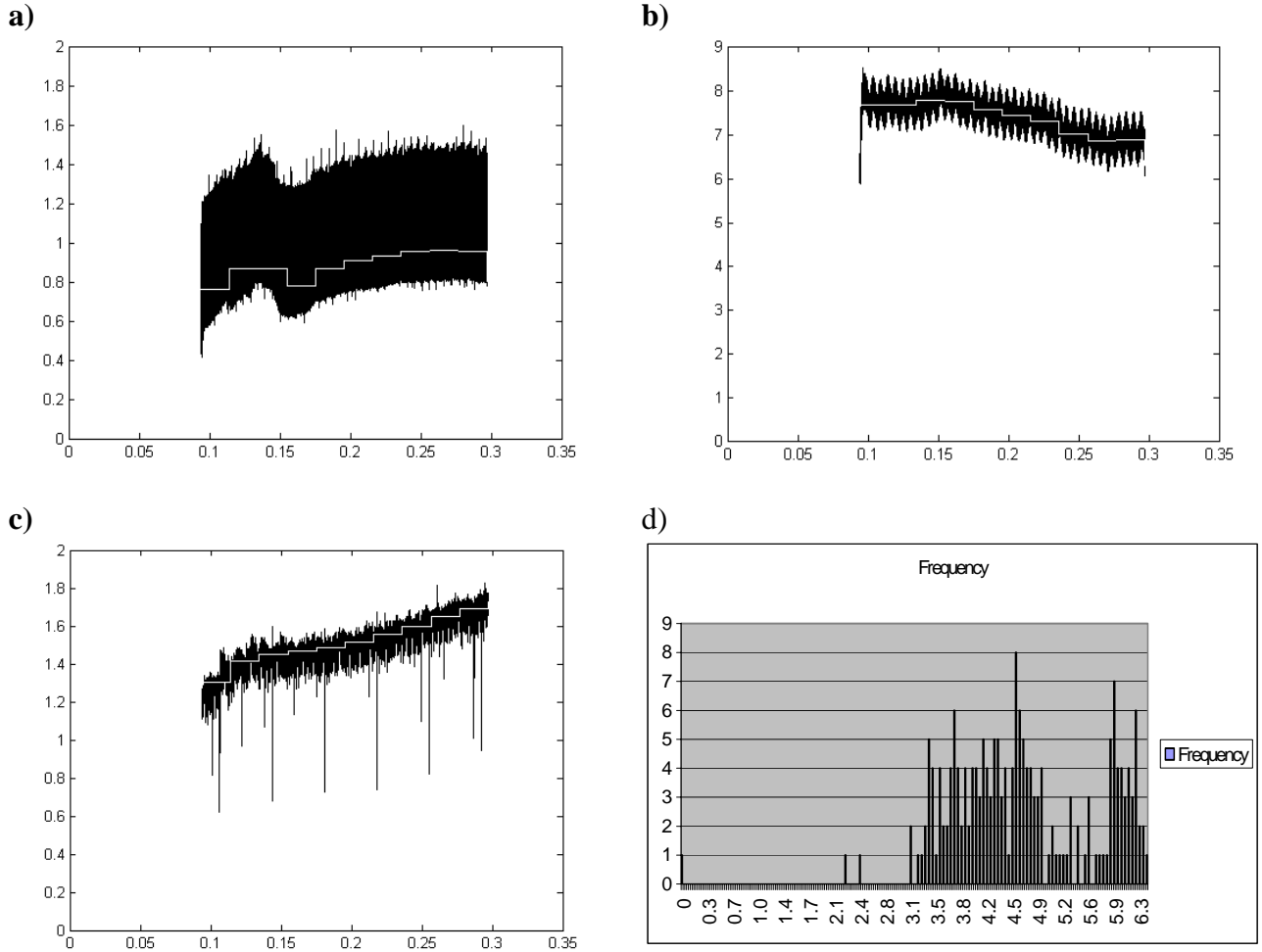


Figure 2: Division into means of ten equal lengthly parts. The black curve stands for the original data and the white curve shows the means. a) voltage signal, b) current signal, c) compression force signal, d) histogram of welding spot diameters.

Method

Self-organising maps were used to interpret the quality of resistance spot welding joints. The self-organising map (SOM) is a neural network method that visualises high-dimensional data in a two-dimensional space. The SOM presents the statistical dependencies of high-dimensional data in the form of geometrical figures. 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 high-dimensional space.

The SOM is usually formed of neurons on a regular low-dimensional grid, which lattice is hexagonal or rectangular. 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 by choosing a data sample \mathbf{x} and finding the closest model vector \mathbf{m}_c (the best-matching unit).

When the best-matching unit is found, it and its closest neighbours 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 neighbourhood kernel centred on the winner unit c . The training continues by choosing a new data sample and by iterating the updating equation.

For more information on self-organising maps, [Kohonen] is recommended.

Results

The study was mainly based on the means of ten equally long parts of the continuously measured signals. The legends used in this study are: c = current, f = force and v = voltage and the numbers $1, \dots, 10$ mark the means of the

respective tenths of the signal divided into ten parts of equal length. The data are described in the chapter “Data description and pre-processing”. In the study, the magnitudes of the signal curve means are compared between the means of equal parts of different signal curves.

The training of SOMs was done in three ways: (1) with a feature set that contained all the means of ten equally long parts of the continuously measured signals, (2) with a reduced feature set that contained only the means with the lowest cross-correlations and the diameter of the welding spot and (3) with a reduced feature set that did not contain the diameter and included only 80 percent of the data.

SOM with all the features

The feature set was compiled by dividing the signals into ten parts of equal length, and the means of these parts

were chosen as features. Also, the size of the diameter was used to train the map. The trained map is shown in Figure 3. The first map in the figure is a u-matrix. The u-matrix displays the distances between the nodes of the map. The nodes, marked with white circles, are the data nodes, and the nodes between them show the distances.

A comparison of the feature maps in Figure 3 shows that different features have similar effects on the diameter of the welding spot. For example, the maps for c_1, c_2 and c_3 are organised similarly. For current and compression force, it seems valid to assume that, if the first feature value (the mean value at the beginning of the signal curve c_1 and f_1) is large, the other feature values (the mean values of the other curve parts) are also large. Because of the mutual correlations, the number of features is reduced. The remaining features with the lowest correlations are: v_2, v_3, v_4, v_5, v_8, c_2, c_7, f_2 and f_9.

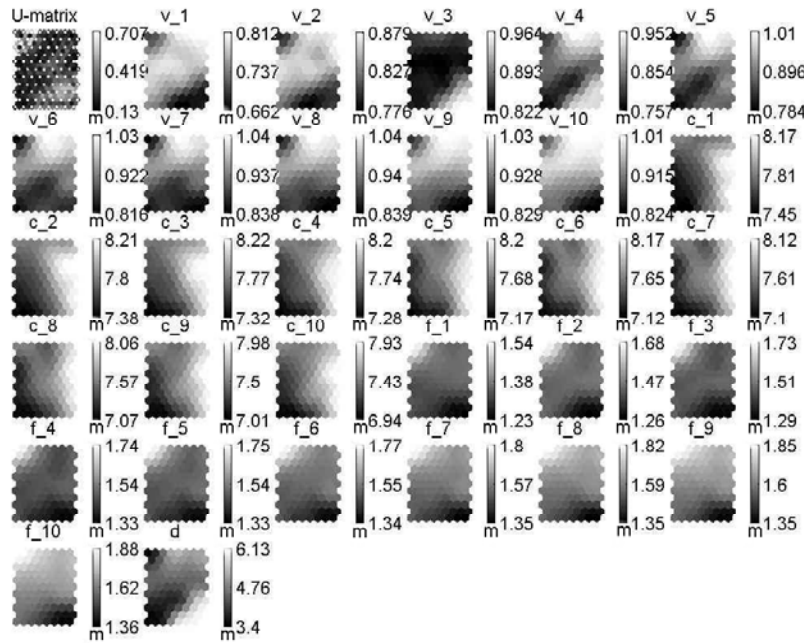


Figure 3: The trained map when the means of ten equally long parts and the diameter were used as features. The following abbreviations are used: c = current, f = force and v = voltage. The numbers 1,...,10 mark the means of the respective tenths of the signal divided into ten parts of equal length.

SOM with reduced feature set

The map in Figure 4 was trained with the remaining features having lowest cross-correlations. A comparison of the last feature map of diameter to the other maps shows that small values of compression force have a positive effect on diameter. Large values of diameter and small values of force occur in the bottom right corner. All the largest values of voltage v_3 also occur in that corner.

The small values of diameter appear at the top of the feature map. The features that affect the diameters in that corner are the smallest values of voltage, v_4 and v_5. The smallest values of current in the upper right corner and the largest values of force in the upper left corner also contribute to small values of diameter.

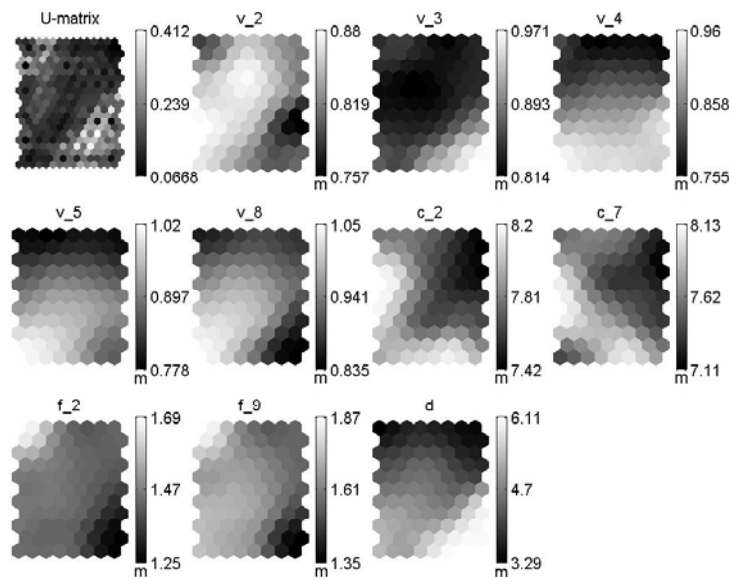


Figure 4: The trained map when the most different features of signals and diameter are used as the training parameters.

SOM for classification

The map in Figure 5 was trained with the same parameters to test the assumption formed on the basis of Figure 4, but using only 80 percent of the data for training the SOM and 20 percent for testing. The difference with training parameters was that diameter was not used as a training parameter. If the size of the diameter is one of the training parameters, it is natural that it affects the formation of the map. To prevent skewing of the map by the size of the diameter, the map is trained without the diameter. In this way, the relation between the diameter of the welding spot and the features extracted from the welding signal curves can be tested without skewing. When training the map without the diameter as a training parameter, the diameter labels are assigned afterwards to the map element representative of the curves that belong to the corresponding cluster. The added labels can be seen in Figure 6 in the appendix.

In Figure 5, the smallest values of force are placed in the upper left corner. When the corresponding labels of the diameters are checked from Figure 6, it can be seen that the largest diameters are also placed in the upper left corner.

Figure 4 also showed that the smallest values of voltage, v_4 and v_5 , interact with the small values of diameter. In Figure 5, these values are in the upper right corner. The smallest values of current occur slightly left of the corner, while the highest values of compression force occur further down. When considering the diameter labels 6, it can be seen that almost all of the unsuccessful welds are in that corner. The assumptions of interaction

between the diameter and the other features made on the grounds of Figure 4 are valid.

In order to obtain more significant results, the data were divided into two parts: training and testing data. The training data consisted of 80 percent of the original data, and they were used to train the map. Figure 6 in the appendix shows the diameter labels, and the grey area contains all the unsuccessful welds. The area was chosen on the basis of the third SOM, and the labels of the training data and the area were used to determine the quality of the welding spots on the basis of the testing data. The white boxes were drawn to point out the successful welds, which are also in the grey area.

Figure 7 in the appendix shows the diameter labels of the testing data. The welds were arranged separately by finding the best-matching unit from the map and adding the diameter label afterwards. Figure 7 shows that all the unsuccessful welds are placed in the grey area derived from Figure 6. Only three successful welding spots were misinterpreted, but they lie at the same nodes as the successful welds in Figure 6.

Depending on the area of application, the division into successful and unsuccessful welds can be changed. If it is important that all the unsuccessful welding spots are found, the division shown in Figure 6 can be used, but if some of the unsuccessful spots can be misinterpreted, the grey area can be smaller. Also, it may be useful to divide the map into three categories: successful spots, unsuccessful spots and spots that need to be tested in more detail.

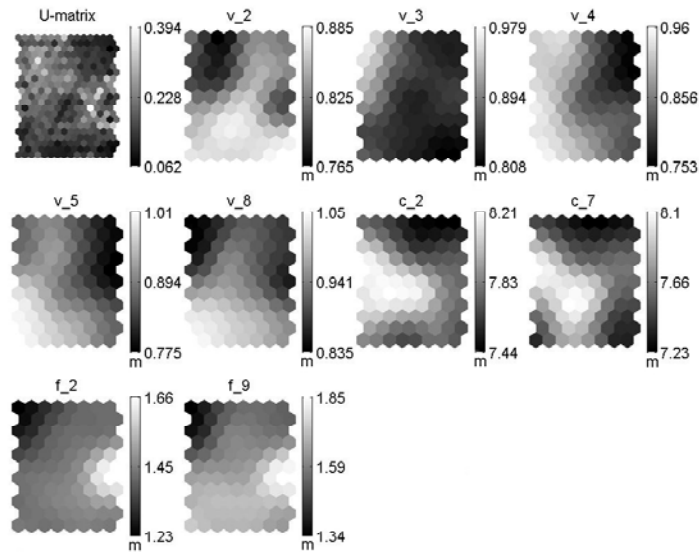


Figure 5: The trained map when the most different features of signals are used as the training parameters.

Conclusions

The quality of welding spots was interpreted using self-organising maps. The data contained measured signals of current, compression force and voltage recorded during the welding process and the size of the diameter measured after the welding. The approach clearly revealed a correlation between the features extracted from these variables and the quality measure. The results of this study can be considered to suggest new approaches to the study of quality, but the adoption of the results into industrial use requires additional tests.

The SOMs were trained with a feature set that contained the means of the signal curves divided into ten parts of equal length and a feature set with the most similar features removed. The observed relations between quality and the features were that the small values of compression force affected positively and the small values of voltage, v_4 and v_5 , negatively the size of the diameter. Small values of current and large values of compression force were also related to small values of diameter. Furthermore, the quality of welding spots can be inferred on the basis of SOMs trained with other welds, as shown by our decision to divide the data into training and testing data.

The analysis of welding curves with SOMs, as proposed in this paper, has proven its analytical power by revealing the dependency of weld quality on welding current and electrode force without any *a priori* process knowledge. In further investigations, more detailed relations within the welding process can be found by SOM analysis of more respectively sampled data.

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Appendix:

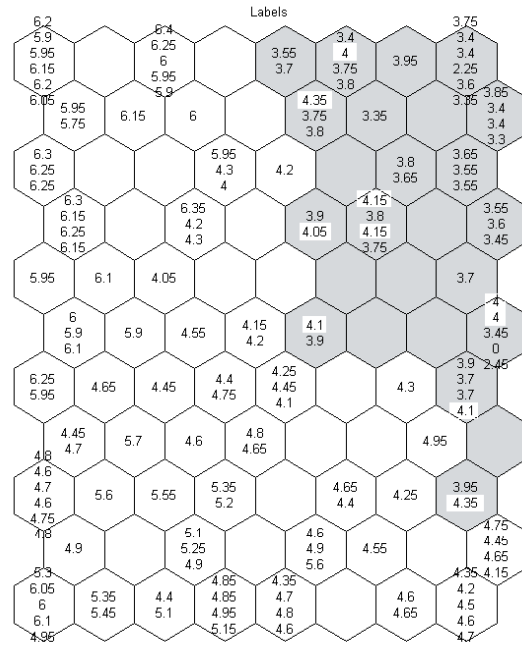


Figure 6: The labels for the map seen in Figure 5.

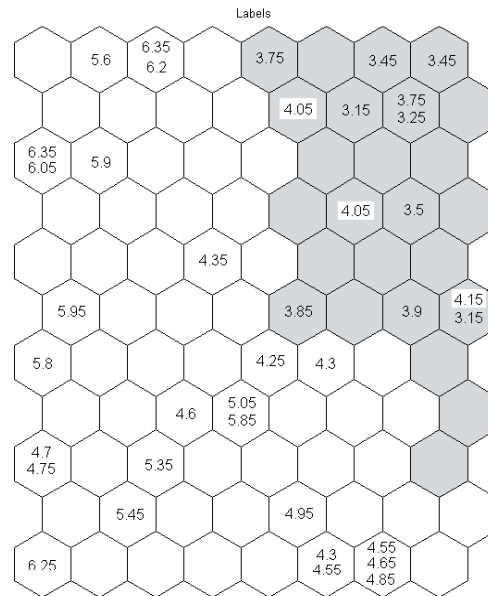


Figure 7: The labels for the testing data.

Short CV of authors

Heli Junno was born in Kuivaniemi, Finland, on June 24th, 1979. She works as a research assistant in Intelligent Systems Group and has been working in the group for 1,5 years. During this time she has been actively developing new computational techniques for welding spot quality assessment. Heli is a student of mathematics in the University of Oulu. After graduation her goal is to pursue her studies towards doctoral degree in information processing. Heli's main extracurricular interest is taekwondo.

Perttu Laurinen was born in Nurmes, Finland, on November 26th 1974. He graduated from the University of Oulu, Department of Mathematics, in 2000. In his studies he specialized in statistics. At the moment he is a researcher at the Intelligent Systems Group and a PhD student in the national Graduate School for Electronics, Telecommunication and Automation (GETA). His main research interest is applying data mining techniques in industrial applications. Perttu's main extracurricular interest is sports.

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Juha Rönning received his Diploma in Engineering (MSEE) degree, Licentiate in Technology with honours, and Doctor of Technology from the University of Oulu, Department of Electrical Engineering, in 1983, 1985 and 1992, respectively. From 1983 onwards, he has been a member of the Faculty of Technology in the University of Oulu, where he is currently professor and head of Department of Electrical and Information Engineering. In 1985, he received an Asla/Fulbright Scholarship. In 1985 and 1986, he was a visiting research scientist in the Center of Robotic Research at the University of Cincinnati. During 1986-1989, he was a junior researcher for the academy of Finland. His main research interests are in intelligent systems, especially mobile robots, and machine vision. He is a member of SPIE, IEEE, Sigma Xi, Finnish Pattern Recognition Society, and Finnish Artificial Intelligence Society (FAIS).