Application of the Extended $k$nn Method to Resistance Spot Welding Process Identification and the Benefits of Process Information

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***Abstract*— Resistance spot welding is used to join two or more metal objects, and the technique is in widespread use in, for example, the automotive and electrical industries. This paper introduces the use of the k-nearest neighbours ($k$nn) method to identify similar welding processes. The two main benefits achieved from knowing the most similar process are: (1) the time needed for the set-up of a new process can be substantially reduced by restoring the process parameters leading to high-quality joints, and (2) the quality of new welding spots can be predicted and improved using the stored information of a similar process. In this study, the basic $k$nn method was found to be inadequate, and an extension of the $k$nn -method, called similarity measure, was developed. The similarity measure provides information of how similar the new process is by using the distance to the k-nearest neighbours. Based on the results, processes can be classified, and the similarity measure proved to be a valuable addition to the existing methodology. Furthermore, process information can provide a major benefit to welding industry.**

***Index Terms*— Similarity, past cases utilisation, initialisation parameters, quality control, process drift.**

I. Introduction

RESISTANCE spot welding is used to join metal objects. It is widely used in, for example, the electrical and automotive industries. Figure 1 shows an example where two metal sheets are welded together. Electrode force is applied to hold the electrodes tightly together, and an electrical current is passed through the electrodes and the material. The resistance of the material being welded is much higher than the resistance of the electrodes. Thus, enough heat is generated to melt the metal. The pressure on the electrodes forces the molten spots in the two pieces of metal to unite and thereby to form the final spot (nugget).

The principle of this study can be seen in Figure 2. At first, data from a new process are gathered and pre-processed. Previously collected data from different processes are already available in a database. The new data are compared with the data stored in the database and the most similar process is identified (process identification). After that, the similarity measure is calculated between the new data set and the most similar process. If the processes are classified as similar based on the similarity measure, the database restores the process parameters leading to high-quality joints (the time needed for the set-up of a new process can be substantially reduced) or the methods optimal for quality control and improvement. The methods that were developed for a similar process work well enough with the new process.

In this study, the term ’process’ is used to refer to a welding event where certain materials are welded together using certain machines and controllers. The parameters assigned to welding machines can vary within a process, but if, for example, the thickness of the metal sheets changes, the welding event is categorised as a new process. Hence, ’process’ could also be defined as ’production batch’.

The emphasis of this study is on process identification, the similarity between any two processes and the benefits of process information. The $k$nn method was used to find the most similar process, and an extension of the $k$nn method was developed to find out if the most similar process could be classified as similar. The idea of process identification was introduced for the first time in [1]. Further research has since been carried out, and this study is a follow-up on the authors’ second article on process identification, where different classification methods were discussed [2]. In addition, an early version of this study was reported in [3]. However,

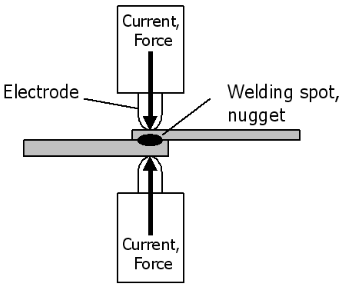

Fig. 1. Spot welding.

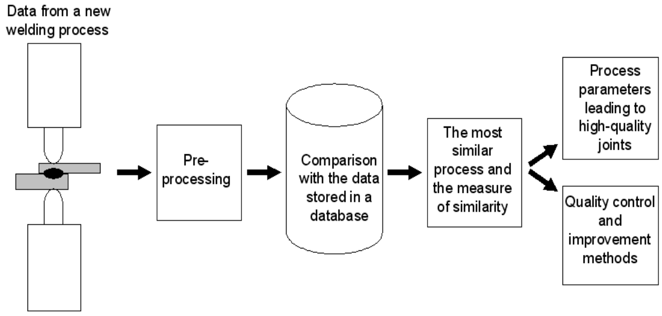

Fig. 2. The principle of the study.

the benefits of process identification are discussed in more detail here. Moreover, the database built to support this study is reported in [4].

The research in the field of spot welding has concentrated merely on estimating the quality of welding spots or on improving the process by modelling the performance of some individual elements of the spot welding system. The studies have approached the problem only for one process at a time, and the information of previously run similar processes has not been utilised. Studies have been made with neural networks, regression analysis and mathematical methods using different features extracted from data. The variation of resistance over time (dynamic resistance pattern) has been an important explanatory variable in many studies. Artificial neural network and regression models were generated based on the dynamic resistance pattern in, for example, [5], [6] and [7]. The approach of [7], where the Hopfield network was used to classify new experiments into five different classes (two of them consisting of unsuccessful welds), lacks reliability because the test set comprised only ten experiments. In addition, dynamic resistance [8] and electrode indentation measured from servo gun [9] has been used to monitor welding processes online. However, the data sets in these studies were also small, consisting of merely under 40 experiments. In addition, dynamic power factor in spot welding is modelled to improve the quality of welding process [10]. 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 [11]. Pre-weld information, such as angular misalignment and fit-up faults of the electrodes, have also been used [12]. In addition, studies using self-organising maps [13] and Bayesian networks [14] have been made.

This article is organised as follow. In the chapter II, the data set used and the pre-processing criteria are introduced in detail. The chapter III explains the k nearest neighbours method and how it is extended to suit the identification of different spot welding processes. The chapter IV points out the most important results, and it consists of two sections: the process identification section and the section describing the benefits of process identification. The conclusions are reported in the last chapter.

II. Data description and pre-processing

In this study, the data set was provided by two welding machine manufacturers: Harms + Wende GmbH & Co.KG (HWH) [15] and Stanzbiegetechnik (SBT) [16]. The HWH tests were made on materials commonly used in the automotive industry, while SBT concentrates on welding thin materials used in electronic components. A more detailed list of the materials is given in Table I. As regards Table I, it should be noticed that the values given for the thicknesses of the material 2 of SBT1-SBT5 actually apply to the areas of the joint parts.

The data set contained altogether 3879 experiments from 20 processes (11 from HWH and 9 from SBT, and they are marked as HWH1-HWH11 and SBT1-SBT9). The experiments were welded using varying welding parameters, and each experiment consisted of measurements of current and voltage signals recorded during the welding process. The processes have been divided into several configurations. The term 'configuration' refers to a set of experiments (usually 15 experiments) welded with unchanged parameters. For example, the experiments measured with current values of 8.0kA, 7.2kA and 6.4kA while the other parameters remained unchanged constituted three different configurations. The parameters that varied between the configurations were current, electrode force, electrode wear and fitting. It should also be noticed that the configurations occurred as separate clusters in the data space (see Figure 4 a) for an example). In this study, the configurations were also used to examine the functionality of the method.

The measured signal curves contained plenty of oscillatory motion and a pre-heating section, and they were hence pre-

TABLE I

MATERIALS USED IN THE WELDING TESTS. IT SHOULD ALSO BE NOTICED THAT THE WELDING MACHINES, CONTROLLERS AND TIMES VARIED BETWEEN THE PROCESSES.

Data	Material 1	Material 1 diameter (mm)	Material 2	Material 2 diameter (mm)
HWH1	Steel DC07	1	Steel ST14	1.5
HWH2	Steel ST07	1	Steel ST07	1.5
HWH3	Steel ST07	1	Steel ST07	1.5
HWH4	Steel ST07	1	Steel ST07	1.5
HWH5	Steel DC07	1	Steel ST14	1.5
HWH6	Steel ST07	1	Steel ST07	1
HWH7	Steel ST07	1	Steel ST07	1.5
HWH8	Steel ST07	1	Steel ST07	1.5
HWH9	Steel DP-K	1	Steel ST14	1.5
HWH10	Steel DC07	1	Steel ST14	1.5
HWH11	Steel ZSTE260Z	1	Steel ST14	1.5
SBT1	X12CrNi17 7	0.18	AGNi 10/Ni	0.5x0.9mm2
SBT2	X12CrNi17 7	0.18	AGNi 10/Ni	0.5x0.9mm2
SBT3	NiBe	0.18	AGNi 10/Ni	0.5x0.9mm2
SBT4	NiBe	0.18	AGNi 10/Ni	0.5x0.9mm2
SBT5	NiBe	0.18	AGNi 10/Ni	0.7x1.5x2.3mm3
SBT6	AgNi10 & CuNi30Fe	1.13	CuBe2	0.2
SBT7	AgNi10 & CuNi30Fe	1.13	CuBe2	0.2
SBT8	CuBe2	0.2	CuNi44	0.6
SBT9	NiBe	0.18	AgNi90/10	0.85

processed before further manipulation. The pre-heating parts of the curves were cut off, leaving only the signal curves recorded during the actual welding phase. In addition, the curves were smoothened using the Reinsch algorithm [17], [18]. After pre-processing, suitable features were extracted from the signal curves. Every signal was divided into ten parts of equal length, and their averages were chosen as features. The stages of pre-processing and feature extraction are demonstrated in Figure 3.

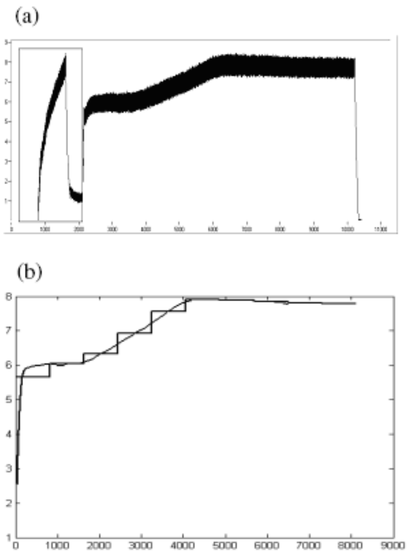

Fig. 3. (a) A raw signal curve. The pre-processing section is outlined with a rectangle. (b) The curve after smoothening and means of the signals calculated on ten intervals of equal length.

III. kNN AND SIMILARITY MEASURE

The k-nearest neighbour classifier was chosen comparatively. In [2], different parametric (quadratic discriminant analysis, linear discriminant analysis and mahalanobis discrimination) and non-parametric (learning vector quantization and k-nearest neighbour classification) classification methods were studied, and the $k$nn method turned out the most suitable due to its accurate results and easy implementation, and it was therefore applied in this study.

The idea of k-nearest neighbour classification is quite simple: a data point is classified into the class in which most of its k-nearest neighbours belong. The nearest neighbours are defined using, for example, the Euclidean distance measure [19].

In this study, information of which process is the closest was considered inadequate. The basic $k$nn classifier identifies the closest process based on the distance but does not indicate how far the process actually is. The database does not comprise an all-inclusive data set of previously welded processes (actually, an all-inclusive data set is impossible to provide). Thus, it should be recognized that some of the new processes can be so dissimilar from the ones already stored in the database that leaving out the distance information would cause serious misclassifications. In [20], distance information is discussed, but for novelty detection of running rotors. In addition, the data used in the study differ remarkably from the spot welding data. In [20], the maximum of the distances to the k nearest neighbours was used as a threshold, while in this study this threshold could not be used due to the nature of the data: different configurations constituted separate clusters, creating a sparse data space for every process, while some of the clusters were very far from each other.

In this study, the idea of similarity was approached by developing two boundaries, so that the form of the data set was taken into account. Both boundaries were calculated using the distance information of the k-nearest neighbour classifier. The final threshold, called similarity measure, was a combination of these boundaries.

The first boundary was created to find if new data points are situated among the data points of a configuration. This would mean that the processes could be classified as the same. In practice, the average distance between the data points and their k (k=5) nearest neighbours within a process was found to be suitable for this task and was thus chosen as the first boundary. The value of k was the same as the value used in the rest of this study.

A simplified example of the first boundary is presented in Figure 4 (a) and (b). Actually, the data set was 20-dimensional, but the idea is presented here using a two-dimensional figure. The white points refer to measurements from two different configurations of a process. The difference in current between the configurations is 10 percent (8.0kA and 7.2kA). Figure 4 (a) shows the average distance to the k (k=2) nearest neighbours for three data points (slashed circles). Figure 4 (b) demonstrates the actual first boundary (the average of the average distances to the k-nearest neighbours). The black points refer to the test points 1-4. The test points demonstrate the new measurements to be classified, and the slashed circles around them mark the boundary. It can be seen that, by using the first boundary, the test point 2 would be classified as the same process compared to this process.

The next step is to classify the points 1, 3 and 4 in Figure 4 (b). It seems obvious that the test points 3 and 4 are also from the same / a similar process, but from neither of the configurations. In addition, the test point 1 seems to be too far to be classified as similar. The second boundary is formed to solve this problem.

The average distance to the k-nearest neighbour between two neighbouring configurations was chosen as the second boundary. In a simplified manner, the boundary could be pictured as the radius of a sphere around the configurations of a process. Test data falling inside the sphere (the average distance to the k-nearest neighbours of a configuration is inside the boundary) would be classified as similar. In addition, the boundary was to satisfy two requirements: 1) to avoid classifying dissimilar processes as similar, and 2) to classify test data falling between two neighbouring configurations of the same process as similar.

The study was carried out by selecting two neighbouring configurations, between which the average distance was calculated, to define the second boundary. The boundary was formatted to fit the spot welding data available and the data

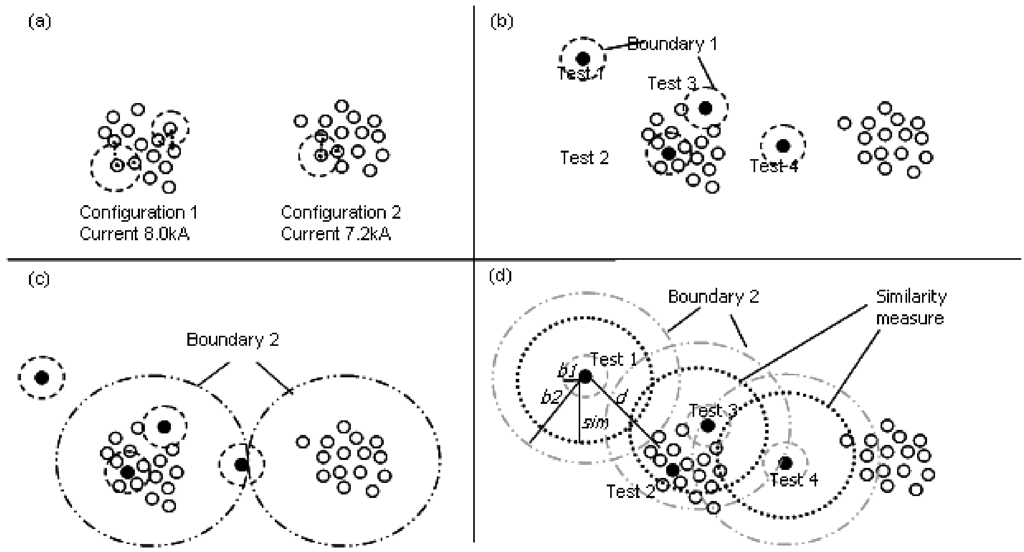

Fig. 4. A simplified example of the boundaries

to be gathered in the future. Thus, the configurations chosen differ merely with regard to the initialised current (current was the only parameter that varied between the configurations in every process and can be assumed to vary in future processes).

The second boundary (i.e. the radius of the sphere) was defined in such a way that the boundaries of two neighbouring configurations would overlap only minimally (requirement 1), but would cover the whole area between the configurations (with the spheres touching each other, requirement 2). Because the values of current between the configurations of different processes varied between 5 and 10 percent, the percentage between the configurations fulfilling these requirements in every process was considered as 5 percent (half of the biggest gap).

An example of the second boundary can be seen in Figure 4 (c) and in Figure 4 (d). In Figure 4 (c), the large slashed circles demonstrate how the second boundary is approximately placed relative to the configurations. The final situation is shown in Figure 4 (d), where both boundaries are marked around the test points.

It was mentioned above that the 5 percent between the two neighbouring configurations was half of the biggest gap. Thus, the average distance to the k-nearest neighbours between the configurations with 5 percent variation in current had to be calculated for every process. The calculation could be done soundly, because when the current varied between the configurations, the change of the average distance in the feature space was approximately linear.

The final similarity measure combines the information of the boundaries and provides a more straightforward result to be used in industry. The final form of the similarity measure was obtained by comparing these two boundaries with the average distance from the data points of a new test set to the k-nearest neighbours of the closest matching process. If the new distance is marked as d and the boundaries are marked as $b1$ and $b2$, then the similarity measure sim is

$$sim = \frac{d - b1}{b2 - b1}. \tag{1}$$

Now the thresholds for the similarity measure can be formulated more concretely. If the similarity value is smaller than zero, the new test set is considered to be precisely the same process as the closest matching process. If the similarity measure is between zero and one, the closest process is considered similar, and knowledge of that process can be used as tentative information of the new test set. If the similarity value is greater than one, the closest matching process is classified as dissimilar.

IV. Results

A. Process identification

In this chapter, process identification is introduced in more detail. Each configuration of different processes is successively considered as a new data set and compared to the information stored in the database. However, the information of the process to which the configuration belongs to is not taken into account in the comparison. Hence, the setting of the experiment resembles the actual operation of the system.

The value for k was chosen using cross-validation. The values 1 and 3 gave the best results, but the third best value of 5 (difference insignificantly small compared to the values 1 and 3) was chosen to give robustness to the method.

In this paper, three of the processes are introduced in more detail. These three processes represent the data sufficiently, and the introduction of the results of the other processes would be duplication. The eleven HWH processes are mutually quite similar, and it is therefore adequate to discuss only one of them more thoroughly. However, the data set of SBT also contains processes known to be very different from each other, and hence one of each case (processes similar and processes dissimilar) is introduced in more detail. The processes now presented are HWH2, SBT3 and SBT4. A further interesting,

TABLE II
CLASSIFICATIONS OF THE FIRST SEVEN CONFIGURATIONS OF (A) HWH2, (B) SBT3 AND (C) SBT4

(a)

Configurations of HWH2	**HWH3**	**HWH4**
C1: Percentage Similarity measure	100 0.49	
C2	93.3 0.37	6.7 1.02
C3	13.3 0.32	86.7 0.79
C4	100 0.88	
C4	100 0.21	
C4	100 0.35	
C4	100 0.44	

(b)

Configurations of SBT 3	**SBT 9**
C1: Percentage Similarity measure	100 0.89
C2	100 0.86
C3	100 0.89
C4	100 0.86
C4	100 0.89
C4	100 0.89
C4	100 0.39

(c)

Configurations of SBT 4	**SBT 9**
C1: Percentage Similarity measure	100 2.61
C2	100 2.97
C3	100 3.08
C4	100 3.08
C4	100 3.11
C4	100 3.14
C4	100 3.00

although not surprising, point is that the SBT and HWH processes do not blend with each other.

Table II shows the results obtained for the three processes. Only the first seven configurations of each are represented to avoid duplication. The abbreviations C1-C7 mark different configurations. In addition, the first number of cells indicates the percentage of data points of a configuration classified as each process, while the second number is a value of the similarity measure.

The HWH2 case in Table II (a) indicates that most of the configurations are classified with 100 % accuracy as HWH3. The configurations C2 and C3 are exceptions to this. For example, 93.3 percent of the experiments of configuration C2 are classified as process HWH3 and 6.7 percent as process HWH4. In this case, the similarity measure is also better for HWH3. However, most of the experiments in configuration C3 are classified as HWH4, while the similarity measure is remarkably smaller for HWH3. Hence, the user needs to decide which should be considered more important, a small value of the similarity measure or a large classification percentage. However, the developed system shows both the similarity and the percentage, which enables the user to make the decision by applying information of both processes and choosing the most suitable alternative.

In the SBT data set, all the processes were classified with 100 % accuracy. However, the similarity measure showed that some of the closest processes were further than the others. An example of two processes known to be approximately the same is shown in Table II (b). The processes SBT3 and SBT9 are similar to each other, but the SBT9 process was welded one year later. Table II (b) shows the classification results for SBT3. It can be seen that the similarity measures for all configurations are smaller than one, and the processes are therefore classified as similar. The positive thing in this example is that the method can identify these similar processes, though the conditions may vary considerably during one year of operation.

An opposite example can be seen in Table II (c) for the process SBT4, for which there are no similar processes stored in the database. The similarity measures give the same information. The configurations of the process SBT4 are classified as SBT9, but the similarity measures are much larger than one. These two processes are classified as dissimilar using the similarity measure, which result was also desired.

B. Benefits of process identification

Process information can be used to restore the manufacturer's correct initialisation parameters for welding machines or to find suitable quality control and improvement methods developed for previously gathered data. The next two sections will show simple examples of how this can be done and point out the benefits.

1) Initialisation parameters: When a similar process is found, the database is searched and the parameters leading to high quality joints are restored. This approach can substantially reduce the set-up time of a new process. In practice, even experienced welding machine users must find the suitable parameters through trial and error. Naturally, this means spending more time and money, while the system developed here can restore the parameters faster and more automatically. The final aim of the system is to gather vast amounts of information from different manufacturers into a database from which suitable initialisation parameters can be searched independent of the manufacturer. Thus, when a manufacturer begins to weld new parts (expertise needed to select the suitable parameters is not found inside the factory) the initialisation parameters already used in different factory can be found from the database.

2) Quality control and improvement: The quality control and improvement methods that already exist can be used for a new process if the process found is classified as similar. A simple example of quality prediction can be seen in Figure 5. The average quality of the k closest data points of a new experiment is assigned as a quality value of the experiment. In this case, the closest data points for both SBT3 and SBT4 were found from SBT9. Figure 5 shows, for clarity, only the predicted and the actual measured qualities for different

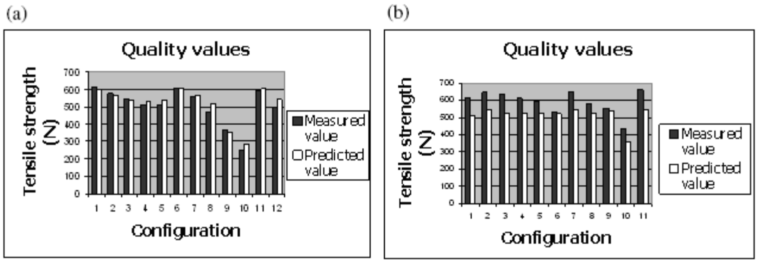

Fig. 5. Average measured and predicted quality values of experiments by different configurations of (a) SBT3 and (b) SBT4.

configurations (not for individual experiments). It can be seen that the measured and predicted values of SBT3 correspond well to each other. In practice, if even such a rough prediction can give a good estimate of quality, provided the processes are similar enough, it can be assumed that more sophisticated methods could give even more accurate results. Naturally, because the similarity measures were so poor for SBT4, the results are remarkably worse. The quality information of the closest matching process cannot be used, but because the similarity measure is known, this mistake would not be made.

Figures 6 and 7 show an example of a quality improvement method called detection and visualisation of process drifts. The basic idea for one process is introduced in [21]. In this case, the self-organising map is trained using information of a similar process (to be precise, HWH3, Figure 6), while the map is also used to detect and visualise the process drifts of the process HWH2 (Figure 7). Figure 6 (a) shows the U matrix, while Figures (b) and (c) show the map as labelled. The labels in b) demonstrate the different configurations; the label ref represents the reference parameters: 8.0 kA for current and 3000 N for electrode force, and the abbreviation ne refers to a new electrode, while ew refers to electrode wear a.k.a. old electrode. In addition, the abbreviation $c-10\%$ means a current decrease of 10 percent, $f+10\%$ means an increase of electrode force, and fit is used for different fitting setups. Figure 6 c) demonstrates successful (marked as 1) and unsuccessful (marked as 0) welding experiments. It can be seen that the unsuccessful welds are located in the left upper and lower corners.

The grey area in Figure 6 (b) is used to mark the place where the highest quality welding spots are situated. The idea of process drift detection is to find out when the new welding tests began to drift from this grey area and to prevent this drift by, for example, increasing the current.

The labels demonstrated in Figure 7 are the labels for the quality and configurations of HWH2, which are assigned to the map elements of HWH3. The same grey area is also used for

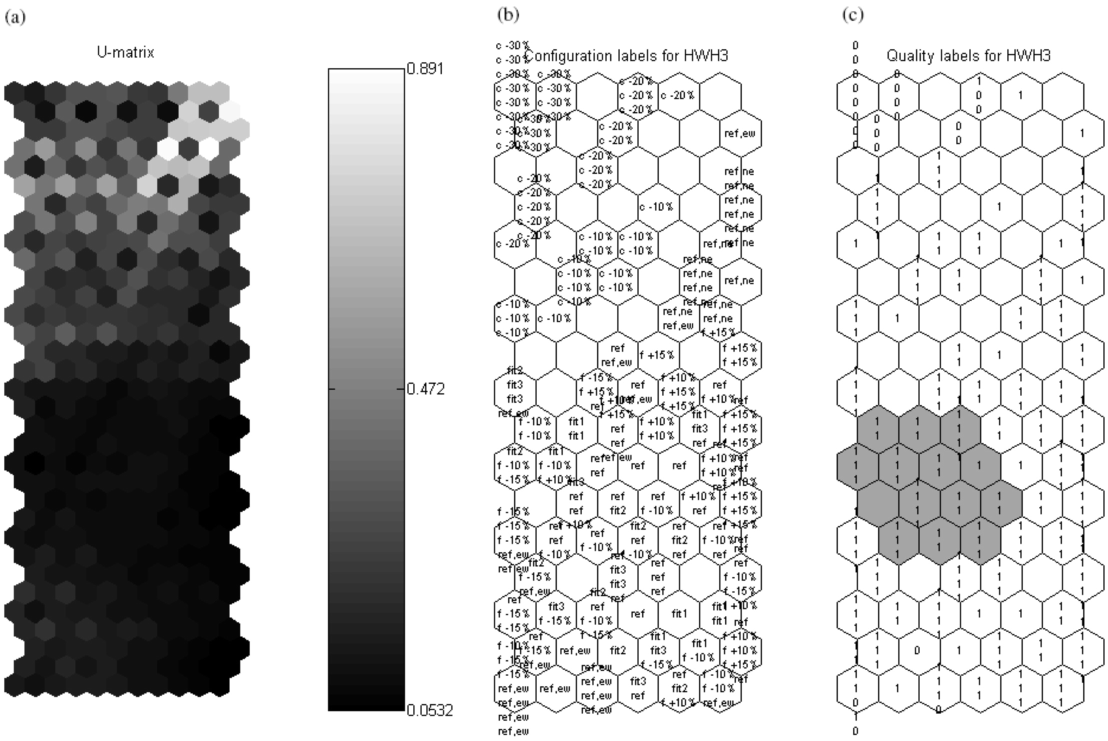

Fig. 6. Self-organising map for process drift detection and visualisation (HWH2).

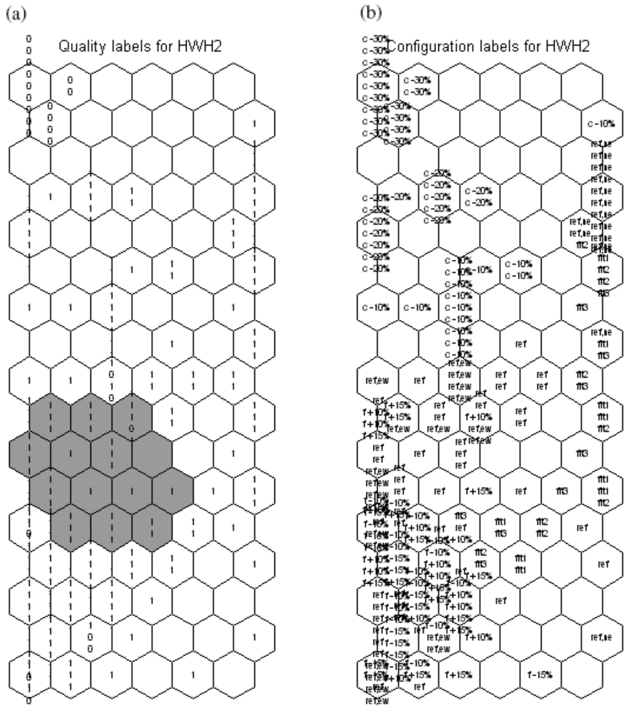

Fig. 7. Self-organising map for process drift detection and visualisation (HWH3).

process drift detection for the welding experiments of HWH2. It can be seen that the unsuccessful welding experiments of both processes are situated in approximately the same areas. This means that a previously trained map for the similar process can help to improve the quality of the welding spot of a new process. However, it has to be noticed that some of the unsuccessful welds of HWH2 are situated near, or even within, the grey area. A closer study indicates that these unsuccessful welds are caused by worn electrodes. However, there are also unsuccessful welds of HWH2 caused by worn electrodes in the lower left corner. When the system detects drift towards that corner, the current is increased and unsuccessful welds no longer occur. Naturally, in some cases, when the drift towards electrode wear labelled areas is recognized, the worn electrodes can be replaced.

V. Conclusion

The main focus of this study was on process identification of different welding processes and the benefits achieved by knowing similar process. The most similar welding process was identified using the k-nearest neighbour method, and the actual similarity was decided using a similarity measure, a measure developed as an extension to $k$nn. With the similarity measure, it could be decided whether a similar enough process is already stored in the database or whether a more extensive data set is needed. The results showed the effectiveness of the extended $k$nn method; processes known to be similar were classified as similar, while dissimilar processes had similarity measures larger than one.

In addition, the benefits of process information were discussed in more detail. Self-organising maps trained for similar processes can be used to detect and visualise the process drifts of new processes, which improves the quality of the welding spots of new processes. It can be concluded that, with the help of the developed system and by knowing the similar process, correct initialisation parameters can be provided to the manufacturer, or the quality of welding spots can be predicted or improved.

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References

[1] H. Junno, P. Laurinen, E. Haapalainen, L. Tuovinen, J. Röning, D. Zettel, D. Sampaio, N. Link, and M. Peschl, “Resistance spot welding process identification and initialization based on self-organising maps,” *Proceedings of 1st International Conference on Informatics in Control, Automation and Robotics*, vol. 1, pp. 296–299, 2004.

[2] E. Haapalainen, P. Laurinen, H. Junno, L. Tuovinen, and J. Röning, “Methods for classifying spot welding processes: A comparative study of performance,” *Innovations in Applied Artificial Intelligence*, pp. 412–421, 2005.

[3] H. Junno, P. Laurinen, E. Haapalainen, L. Tuovinen, and J. Röning, “Resistance spot welding process identification using an extended knn method,” *Proceeding of the IEEE International Symposium on Industrial Electronics*, vol. 1, pp. 7–12, 2005.
[4] L. Tuovinen, P. Laurinen, H. Koskimäki, E. Haapalainen, , and J. Röning, “Building a database to support intelligent computational quality assurance of resistance spot welding joints,” *Proceeding of the IEEE International Symposium on Industrial Electronics*, 2007, to be published.
[5] A. Aravinthan, K. Sivayoganathan, D. Al-Dabass, and V. Balendran, “A neural network system for spot weld strength prediction,” *Proceeding of the UK Simulation Society*, pp. 156–160, 2001.
[6] Y. Cho and S. Rhee, “Primary circuit dynamic resistance monitoring and its application on quality estimation during resistance spot welding,” *Welding Researcher*, pp. 104–111, 2002.
[7] ——, “Quality estimation of resistance spot welding by using pattern recognition with neural networks,” *IEEE Transactions on Instrumentation and Measurement*, vol. 51, pp. 330–334, 2004.
[8] F. Garza and M. Das, “On real time monitoring and control of resistance spot welds using dynamic resistance signatures,” *Proceedings of the 44th IEEE 2001 Midwest Symposium on Circuits and Systems*, vol. 1, pp. 41–44, 2001.
[9] Z. Xiaoyun, Z. Yansong, and C. Guanlong, “Weld quality inspection based on on-line measured indentation from servo encoder in resistance spot welding,” *Proceedings of the IEEE Instrumentation and Measurement Technology Conference*, pp. 1353 – 1356, 2006.
[10] L. Gong, C.-L. Liu, and X. F. Zha, “Model-based real-time dynamic power factor measurement in ac resistance spot welding with an embedded ann,” *IEEE Transactions on Industrial Electronics*, vol. 54, no. 3, pp. 1442 – 1448, 2007.
[11] N. Ivezic, J. D. Alien, and T. Zacharia, “Neural network-based resistance spot welding control and quality prediction,” *Proceedings of the Second International Conference on Intelligent Processing and Manufacturing of Materials*, pp. 989–994, 1999.
[12] L. Brown and J. Schwaber, “Identifying operating conditions from pre-weld information for resistance spot welding,” *Proceedings of the American Control Conference*, pp. 1535–1539, 2000.
[13] H. Junno, P. Laurinen, L. Tuovinen, and J. Röning, “Studying the quality of resistance spot welding joints using self-organising maps,” *Proceedings of Fourth International ICSC Symposium on Engineering of Intelligent Systems*, 2004.
[14] P. Laurinen, H. Junno, L. Tuovinen, and J. Röning, “Studying the quality of resistance spot welding joints using bayesian networks,” *Proceedings of Artificial Intelligence and Applications*, pp. 705–711, 2004.
[15] Harms+Wende, “http://www.harms-wende.de, homepage of the company, referenced: 20.2.2007.”
[16] Stanzbiegetechnik, “http://www.stanzbiegetechnik.at, homepage of the company, referenced: 20.2.2007.”
[17] C. H. Reinsch, “Smoothing by spline functions,” *Numerische Matematik*, vol. 10, pp. 177–83, 1967.
[18] ——, “Smoothing by spline functions, ii,” *Numerische Matematik*, vol. 16, pp. 451–454, 1971.
[19] T. Mitchell, *Machine learning*. The McGraw-Hill Companies, 1997.
[20] S. Guttormsson, I. R.J. Marks, M. El-Sharkawi, and I. Kerszenbaum, “Elliptical novelty grouping for on-line short-turn detection of excited running rotors,” *IEEE Transactions on Energy Conversion*, vol. 14, no. 1, pp. 16 – 22, 1999.
[21] D. Zettel, D. Sampaio, N. Link, A. Braun, M. Peschl, and H. Junno, “A self organising map (som) sensor for the detection, visualisation and analysis of process drifts,” *Poster Proceedings of the 27th Annual German Conference on Artificial Intelligence*, pp. 175–188, 2004.
[22] F. Karlsruhe, “http://www.hs-karlsruhe.de, the homepage of the university, referenced 20.2.2007.”

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