Zezwala się na korzystanie z artykułu na warunkach licencji Creative Commons Uznanie autorstwa 3.0

Application of data fusion for welding process diagnostics

Marek Fidali, Wojciech Jamrozik

Institute of Fundamentals of Machinery Design, Silesian University of Technology

Abstract: Arc welding is commonly applied in industry. Assessment of welded joints quality is one of crucial tasks especially in automated applications. Welding parameters like current, voltage, etc., are used very often in welding process diagnostics, but using single signals is not so effective in describing of welding conditions. Research in use of data fusion techniques for welding process diagnostics is presented in this paper. Signal and decision level methods were taken into consideration. The results of the research confirm that the proposed approach has potential for further practical application.

Keywords: welding, diagnostics, signal processing, data fusion

1. Introduction

Welding is a process of joining of two materials (usually metals) permanently and is widely used in various branches of industry. The key target of application of the welding process is to obtain welded joint whose properties are acceptable in context of quality requirements specified in welding standards (ISO 3834). Different destructive and non-destructive methods may be employed for quality control of welded joints.

Automation of welding in many branches of industry caused that methods for non-destructive testing for on-line welded joint quality assessment are subject of many research and industrial applications since many years. On-line assessment of welded joints assumes that welding process can be treated as a dynamic, complex and uncertain system [1], whose inputs are all adjustable welding parameters (e.g. current, arc voltage, wire feed rate, travel speed) and outputs are the quality features of the welded joint connected with properties of the weld and Heat Affected Zone (HAZ). Under such assumption, quality of welded joint can be assessed and controlled in the on-line mode on the based on various process diagnostics strategies [2]. Measuring and monitoring of welding parameters is the solution of welding process assessment which is very effective and applied often. Welding parameters are a source of specific and often complementary information on the realized process. Taking that into account one can conclude that simultaneous analysis of several process signals can increase detectability of the welding process faults rather than analysis of each signal separately.

Data fusion techniques can be used to perform mutual analysis of the signals gathered during the welding process. Data fusion techniques combine data from multiple sensors to reduce the uncertainty and the amount of redundant information preserving relevant information, in the form of a single artificial signal at the same time.

The main objective of the research was to verify advantages of the selected data fusion techniques in identification of the welding process faults.

2. Multisensor Data Fusion

Multisensor data fusion is a domain of science consisting in synergistic combination of data from multiple sensors in order to obtain new data. More reliable and accurate information can be extracted from the new data than could be acquired by processing data from single sensors separately. Data fusion techniques integrate knowledge from different domains of science, like control theory, signal processing, artificial intelligence, probability, statistics, etc. Three categories of data fusion can be distinguished:

1. Data (signal) level fusion – combines the raw data from multiple source signals into a single one;
2. Feature level fusion – requires extraction of different features from the source data – before features are merged together;
3. Decision level fusion – combines results from multiple algorithms to yield a final fused decision.

Multisensor data fusion is applied in military and non-military areas, such as remote environmental monitoring, medical diagnosis, automated monitoring of equipment, robotics, automotive systems [9], monitoring of manufacturing processes and condition-based maintenance of complex machinery [10, 11]. Different multisensor data fusion approaches was also applied for monitoring of arc welding process. It was shown in [3] that multisensor information fusion technology can effectively utilize information from different sensors and yield better result than a single sensor could provide.

In the paper multisensor data fusion was considered on the data and decision levels.

2.2. Fusion of Welding Process Signals

Data level fusion can be realized in different ways, which depend very often on the nature of data. In case of arc welding, process signals like voltage and current can be fused based on the physical characteristics of welding process like linear welding energy $E(t)$ [12] and welding resistance $R(t)$.

These characteristics affect the welded joint properties and are defined in following way:

$$E(t) = \frac{I(t)U(t)}{v(t)} \tag{1}$$

$$R(t) = \frac{U(t)}{I(t)} \tag{2}$$

where: $E(t)$ – linear welding energy [J/m], $R(t)$ – welding resistance [Ω], $U(t)$– arc voltage [V], $I(t)$ – welding current [A], $v(t)$ – welding speed [m/s].

2.2. Fusion of Welding State Classifiers

Classifier fusion in general is a process similar to data fusion. It can be realized on three levels of abstraction: on the label level, on the rank level and on the measurement level. Among simple label level methods, the majority voting has the well-established position. This simple method gives good results in cases of simple voting and plurality. For small and even number of classifiers, it is problematic to apply majority voting, because removing of classifiers is demanded to avoid ties, which prevents decision making. From a practical point of view, measurement level is the most interesting one. On this fusion level, the classifiers give answers in a form of the continuously valued degrees of support for each of the labelled class used. Several methods, containing the registration and aggregation stages, are elaborated and successfully applied in many areas. This type of methods uses the simple arithmetical operators, such as: average, minimum, maximum, product, etc., to fuse classifiers outputs. The main question is, which operator is the best one for the specific problem? The mean and product operators are the most intensively studied ones and it is known the mean might be less precise, but is a more stable combiner. When the conflicted classifier outputs are considered, simple averaging could result in total confusion. From the variety of class-indifferent methods, those based on the Dempster-Shafer theory (DST) of evidence, having clear mathematical foundations, are those most popular.

Classifier fusion was applied for recognition of welding conditions in a way shown in fig. 1.

In the paper, for purposes of classifier fusion, the Dezert-Smarandache theory (DSmT), being an extension of DST was used. Using the DSmT based method, the classifier outputs had to be converted into a Basic Belief Assignment (BBA). Identified classes, describing process conditions $\{S_1, S_2, ..., S_n\}$ (in general denoted as $\{\theta_1, \theta_2, ..., \theta_n\}$) create an exhaustive set Θ called frame of discernment. The hyper power set D^Θ is defined on all elements of Θ using $\cap$ and $\cup$ operators [7]. There are no constraints regarding the exclusivity of Θ elements.

The Basic Belief Assignment (BBA) is a quantitative expression of the belief committed to the elements of D^Θ denoted $m(\cdot)$. It is defined by mapping of the hyper power set D^Θ onto 0,1 where: $m(\varnothing)=0$ and $\sum_{X \in D^\Theta} m(X) = 1$. X is a valid subset of Θ defined in D^Θ. Element with $m(X)>0$ is called a focal element. General belief (Bel) and plausibility (Pl) functions are defined as follows:

$$Bel(Y) = \sum_{X \in D^\Theta, X \subseteq Y, X \neq \varnothing} m(X) \tag{3}$$

$$Pl(Y) = \sum_{X \in D^\Theta, X \cap Y, X \neq \varnothing} m(X) \tag{4}$$

Within the DSmT aggregation of BBAs is mainly made by use of one of the Proportional Conflict Redistribution (PCR) rules. The most sophisticated one is the rule PCR5 and its generalization – PCR5 rule which could be applied to more than 2 sources of evidence [8]. This rule allows the

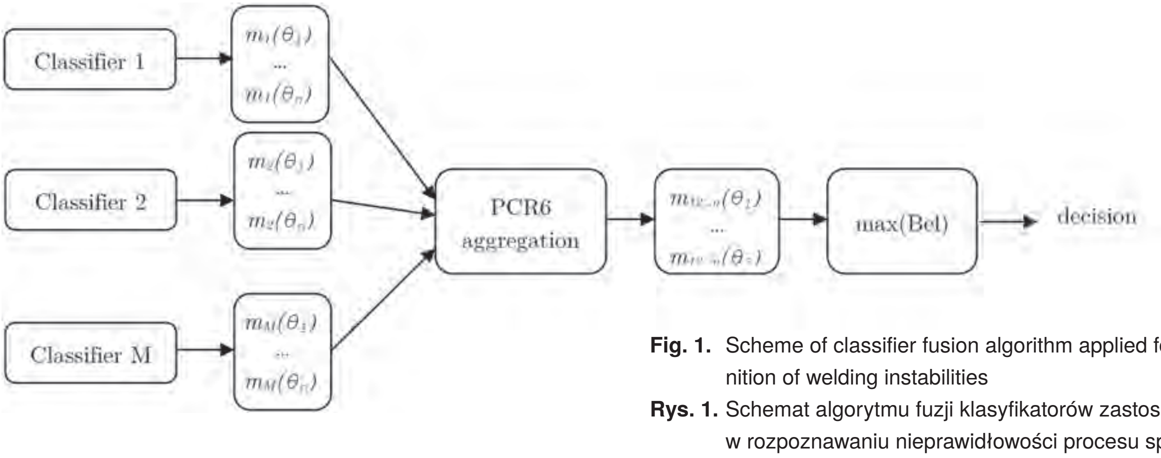

Fig. 1. Scheme of classifier fusion algorithm applied for recognition of welding instabilities

Rys. 1. Schemat algorytmu fuzji klasyfikatorów zastosowanego w rozpoznawaniu nieprawidłowości procesu spawania

Tab. 1. Nominal welding parameters

Tab. 1. Nominalne parametry spawania

Welding current [A]	Arc voltage [V]	Welding speed [cm/mm]	Wire feed rate [m/min]	Shield gas flow [l/min]	Wire tip outlet [mm]
240	25	32	7.4	15	15

redistribution of conflict to all elements of D^Θ involved in the conflict proportionally to their masses (BBAs), so the mass is redistributed locally nor globally as it is in the case of classic Dempster's rule of combination [6]. The PCR6 rule for M sources of evidences, when $X \in D^\Theta$, $X \neq \emptyset$, X is defined by the following expression:

$$m_{PCR6}(X) = m_c(X) + \sum_{i=1}^{M} m_i(X)^2 \sum_{\substack{\bigcap_{k=1}^{M-1} B_{\sigma_i(k)} \cap X \equiv \emptyset \\ (B_{\sigma_i(1)},\ldots,B_{\sigma_i(M-1)}) \in (D^\Theta)^{M-1}}} \left(\frac{\prod_{j=1}^{M-1} m_{\sigma_i(j)}(B_{\sigma_i(j)})}{m_i(X) + \sum_{j=1}^{M-1} m_{\sigma_i(j)}(B_{\sigma_i(j)})} \right) \tag{5}$$

where m_c is the conjunctive rule and σ_i is a factor denying situation that $i=j$. The result of the PCR6 rule is an aggregated BBA representing the joint belief level that is put on each labeled class. Such BBA is a basis for taking the diagnostic decision, which for purposes of presented research was made using the following rule:

$$A = \arg\max_{X \in \Theta} Bel(X) \tag{6}$$

It can be noticed that decisions are only made for elements of Θ not for subsets of Θ that are in D^Θ.

2.3. Active Diagnostic Experiments

In order to verify advantages of data fusion for diagnostic purposes of the arc welding process, series of active diagnostics experiments were carried out.

The experiments were performed using the laboratory stand (fig. 2) equipped with the microprocessor controlled welding machine (WS) Castolin TotalArc 5000, wire feeder (WF), table with trolley for rectilinear welding and measurement system consisting of: sensors for voltage measurement (V), current (A), trolley speed (v) and gas flow (G), connected to the signals conditioning module (D), computer with installed multichannel data acquisition card and the own software for the LabVIEW environment.

During the welding, plates made of steel S235JR (EN 10027-1) with dimensions of 300 mm × 150 mm × 5 mm were joined. The edges of plates were bevelled at the angle of $\alpha = 60°$ and the offset between them was $b = 1.0$ mm. For welding purposes, a solid electrode wire with a diameter of 0.2 mm (Castolin CastoMag 45255) and the M21 shield gas (82 % Ar + 18 % CO_2) were used. Nominal welding parameters are presented in tab. 1.

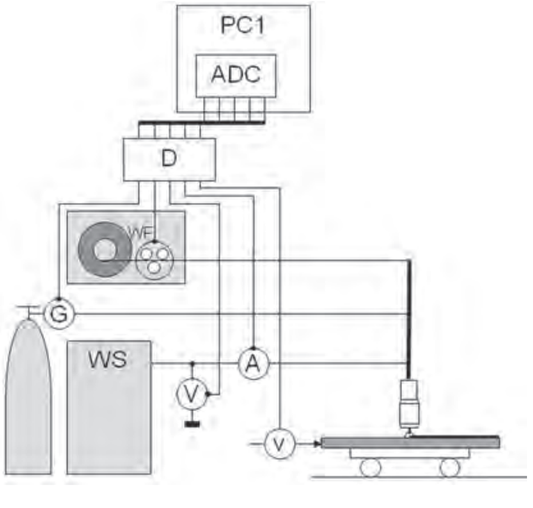

Fig. 2. Experimental setup
Rys. 2. Schemat stanowiska badawczego

Different welding process conditions were simulated during the experiments. This made it possible to record a collection of signals for 8 different process conditions classified as follows:

S1 – correct welding process,
S2 – welding with decay of the shielding gas flow,
S3 – welding of the plates with distinct outbreaks of atmospheric corrosion on the welded surfaces,
S4 – welding of plates with irregularities of the plate edges from side of the weld root,
S5 – welding with deviation of current,
S6 – welding of plates with different offset intervals,
S7 – welding with deviation of voltage,
S8 – welding of the plates with improper welding groove geometry.

Experiments for the same condition class were repeated several times. It was necessary to build the classifiers.

3. Estimation of Signals and Identification of Welding State

Signals acquired during the experiment were fused on the value level according to eq. 1 and eq. 2. New signals can be regarded as coming from the new, virtual sensors.

Process signals of welding current $I(t)$ and arc voltage $U(t)$, as well as new signals $E(t)$ and $R(t)$ were estimated using 16 statistical estimators such as mean value, RMS, standard deviation, kurtosis, skewness etc. Exemplary plots of welding current and voltage, as well as results of its fusion, and resistance signal are presented in figures 3 and 4,

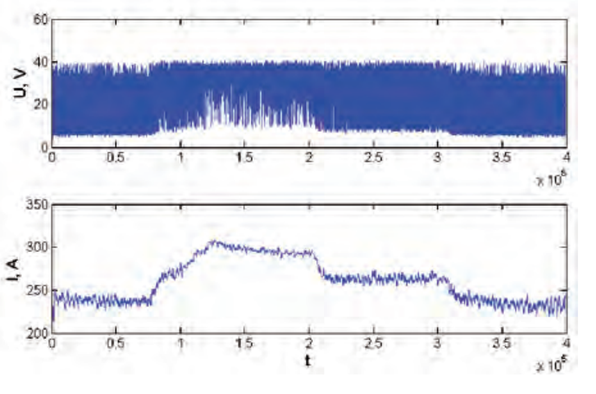

Fig. 3. Exemplary plots of welding voltage and current signals
Rys. 3. Przykładowe przebiegi sygnałów napięcia i prądu spawania

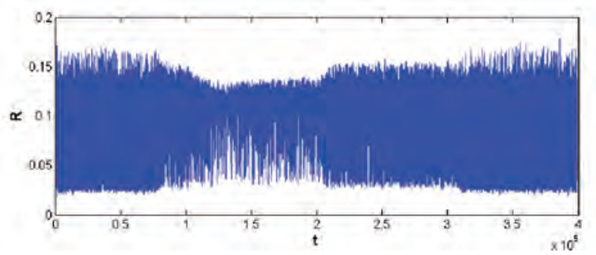

Fig. 4. Plot of resistance signal calculated on the basis of signals presented in fig. 3

Rys. 4. Przebieg sygnału rezystancji spawania wyznaczonego na podstawie sygnałów zaprezentowanych na rys. 3

respectively. Kurtosis of process signals was considered as an important indicator of arc stability, as well as mode of metal transfer in arc welding [4, 5]. Kurtosis is a statistical parameter that indicates the sharpness or smoothness of a signal distribution compared to the normal distribution. The normal distribution has the kurtosis value of three. Kurtosis is defined as follows:

$$K = \frac{\mu_4}{\sigma^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y})^2\right)^2} \tag{7}$$

where μ_4 is the fourth moment about the mean and σ is the standard deviation.

3.1. Classification of Welding State

Features of the considered signals were used for classification of the welding process conditions. Each condition class of welding process was represented by at least 8 examples, thus the classification was carried out using a k-Nearest Neighbours classifier, where the number of neighbours was assumed to be k = 7. Estimation of the classification efficiency was done using the leave-one-out classifier error estimation technique. In this method the whole available feature set, containing N elements was divided into two separate subsets. The training subset contained N-1 elements, whereas, only one element was included into the test subset. The process of learning and testing of the classifier was performed N times, so that each of the examples can be found in the test set. The classification accuracy measure *acc* was the relative number of correct classifications calculated using the following formula:

$$acc = \frac{n_{correct}}{N} \tag{8}$$

where: $n_{correct}$ – is the number of correctly classified test examples representing a particular class of welding condition, N – total number of test examples considered and representing a particular class of welding condition.

Two classification scenarios were taken into consideration:

- use of one classifier, that is working on patterns utilizing one or more types of features,
- use of several classifiers working on patterns consisting one, different for each classifier, type of feature. Classifier outputs were transformed into BBAs and next aggregated using the PCR6 rule (classifier fusion).

In the second scenario, the normalized membership distribution, easy to obtain from k-NN classifier, was assumed to be the sufficient estimate of belief distribution made by a single classifier.

3.2. Comparison of Classifier Efficiencies

The aim of the research was to compare classification results obtained for welding process signals considered separately and after fusion on value and information levels. Table 2 shows results of classification for the kurtosis of voltage C{K_U} and current C{K_I} signals considered separately. Additionally, classification results for space of features of both signals C{K_I; K_U} was presented in the last row. It can be easily seen that the results are poor. Classifier considering kurtosis values of current signals allows only to recognize two simulated welding conditions (S5 and S6) in satisfactory way. In case of arc voltage signals, results of classification are not that much better. Mutual consideration of feature spaces of both signals allowed recognition of more condition classes. Unfortunately, the mean classifier efficiency is worse than it was for the independent signals features. Very poor classification performances result from the small number of examples, as well as from the strong influence of random noise in the considered signals.

Results of classification for feature space of signals fused on the value level, are presented in table 3. A slight (more than 15 %) growth of mean classifier efficiency for separately considered spaces can be noticed. The significant increase of the mean classifier efficiency is observed in case of the mutually considered feature spaces of fused signals C{K_E;K_R}. Although results of classification for the fused signals are better, one can observe that some simulated classes of conditions are still not recognizable (S2, S4).

Classification efficiencies determined for estimated signals of welding process, as well as their fused versions were fused on the information level. Tab. 4 shows classification results for the fused classifiers of features of process signals F{C{K_I};C{K_U}} and fused signals F{C{K_E};C{K_R}} and all considered classifiers. In comparison to results obtained for signals considered independently, only fusion of classifiers of energy and resistance F{C{K_E};C{K_R}} yielded better results. Fusion of all classifiers did not increase mean classification efficiency, but recognisability of welding process conditions was improved. From eight states only one remains unrecognised (S4).

Due to properties of information fusion method, improvement of classifier fusion is possible by the use of classifiers trained over the diverse signal features. It is known that diversity of evidence sources is desirable for fusion on information level. The source of evidence can be specified by series of transformations from the physical source of signal through estimation method and the applied classifier. Therefore, supplementing the feature space with the new signal features could lead to additional and complementary information.

In table 5 results are presented of classifier fusion after considering the additional and commonly known RMS signal features. One can notice a significant increase of the overall classifier efficiency in case of fusion of classifiers working on the basis of kurtosis and RMS values of arc voltage signal.

Tab. 2. Classification results for estimated welding voltage and current signals
Tab. 2. Wyniki klasyfikacji uzyskane na podstawie cech sygnałów prądu i napięcia

Classified features	Welding conditions								μ_{acc}
	S1	S2	S3	S4	S5	S6	S7	S8	
$C\{K_I\}$	0.00	0.17	0.00	0.00	0.86	0.67	0.00	0.00	0.21
$C\{K_U\}$	0.82	0.00	0.00	0.00	0.86	0.33	0.57	0.00	0.32
$C\{K_I;K_U\}$	0.27	0.50	0.14	0.00	1.00	0.33	0.00	0.00	0.28

Tab. 3. Classification results for estimated welding heat input and welding resistance signals
Tab. 3. Wyniki klasyfikacji uzyskane na podstawie cech sygnałów energii liniowej spawania i rezystancji spawania

Classified features	Welding conditions								μ_{acc}
	S1	S2	S3	S4	S5	S6	S7	S8	
$C\{K_E\}$	0.45	0.00	0.43	0.00	0.00	0.33	0.29	1.00	0.31
$C\{K_R\}$	0.73	0.00	0.14	0.00	1.00	0.50	0.57	0.00	0.37
$C\{K_E;K_R\}$	0.55	0.00	0.57	0.00	1.00	0.50	0.43	0.86	0.49

Tab. 4. Classification efficiencies after fusion of considered welding signals on information level
Tab. 4. Sprawności klasyfikacji po operacji fuzji klasyfikatorów sygnałów procesu spawania na poziomie informacji

Classified features	Welding conditions								μ_{acc}
	S1	S2	S3	S4	S5	S6	S7	S8	
$F\{C\{K_I\};C\{K_U\}\}$	0.73	0.00	0.14	0.00	0.86	0.33	0.29	0.14	0.31
$F\{C\{K_E\};C\{K_R\}\}$	0.82	0.00	0.57	0.00	0.71	0.33	0.57	1.00	0.50
$F\{C\{K_I\};C\{K_U\};C\{K_E\};C\{K_R\}\}$	0.64	0.17	0.14	0.00	0.71	0.50	0.57	0.43	0.40

Tab. 5. Results of classifiers fusion after considering additional signals features
Tab. 5. Wyniki fuzji klasyfikatorów po uwzględnieniu dodatkowych cech sygnałów procesowych

Classified features	Welding conditions								μ_{acc}
	S1	S2	S3	S4	S5	S6	S7	S8	
$F\{C\{K_U\};C\{RMS_U\}\}$	0.82	0.50	0.43	0.29	1.00	0.33	0.71	1.00	0.64
$F\{C\{K_U\};C\{RMS_I\}\}$	0.73	0.50	0.86	0.00	0.86	0.33	0.29	0.71	0.53
$F\{C\{K_I\};C\{RMS_I\}\}$	0.45	0.17	0.29	0.14	0.86	0.17	0.00	0.00	0.26
$F\{C\{K_E\};C\{K_R\}\}$	0.82	0.00	0.57	0.00	0.71	0.33	0.57	1.00	0.50
$F\{C\{K_R\};C\{RMS_R\}\}$	0.55	0.67	0.43	0.00	1.00	0.00	0.00	1.00	0.46
$F\{C\{K_E\};C\{RMS_E\}\}$	0.55	0.00	0.71	0.43	0.43	0.17	0.29	0.86	0.43

In this case, all conditions of welding process were recognisable. The worst results were noticed for classifiers of feature space of welding current signal. In the case of energy and resistance signals, application of additional estimators did not improve classification efficiency.

4. Summary

Presented results demonstrate that application of data fusion on different levels can improve noticeably effectiveness of identification of the welding process conditions.

Classification accuracies obtained using classifier fusion are higher than those calculated taking into consideration single classifiers trained over feature space of the fused and not fused signals. It must be mentioned that features chosen for the member classifiers in fusion process should be heterogeneous to assure high classification efficiency.

Moreover, character of estimated signals has a significant influence on classification results. The obtained results demonstrate that arc voltage contains the most important information on welding process instabilities which were simulated during experiments. Poor results obtained on the basis of estimation and fusion of current signal follows from properties of applied welding inverter where current value was controlled by microprocessor and kept around the set nominal value.

The current signal properties affect values of energy and resistance and finally yield the unsatisfactory classification results. It is possible to obtain much better results of welding state identification if preliminary selection of signals and their estimates will be performed, as well as another signal fusion method will be used.

Further research of the authors is focused on search for the effective methods of signals fusion based on welding phenomena and levels of their values.

Acknowledgments

The investigations were partially financed from resources assigned to science in the years 2009–2012 as a research project N504281937 and from resources assigned to statutory activity of Institute of Fundamentals of Machinery Design, Silesian University of Technology at Gliwice.

Bibliography

1. Zhang Y.M. (ed.), *Real-Time Weld Process Monitoring*, Woodhead Publishing 2008.
2. Korbicz J., Kościelny J.M., Kowalczuk Z., Cholewa W. (eds.), *Fault Diagnosis*. Springer-Verlag 2004.
3. Bo Chen, Jifeng Wang, Shanben Chen, *A study on application of multi-sensor information fusion in pulsed GTAW*. "Industrial Robot: An International Journal", vol. 37 is. 2, 2010, 168–176.
4. Pal K., Bhattacharya S., Pal S.K., *Prediction of metal deposition from arc sound and weld temperature signatures in pulsed MIG welding*. "Int. J. Adv. Manuf. Technol.", vol. 45, 2009, 1113–1130.
5. Wu C.S., Gao J.Q., Hu J.K., *Real-time sensing and monitoring in robotic gas metal arc welding*. "Meas. Sci. Technol.", 18, 303, 2007.
6. Shafer G., *A mathematical theory of evidence*. Princeton University Press 1976.
7. Dezert J., Smarandache F., *DSmT: A New Paradigm Shift for Information Fusion*. "Proceedings of Cogis '06 Conference", Paris 2006.
8. Martin A., Osswald C., *A new generalization of the proportional conflict redistribution rule stable in terms of decision*, [in:] F. Smarandache and J. Dezert (eds.), *Applications and Advances of DSmT for Information Fusion, Book 2*, American Research Press Rehoboth, 2006, 69–88.
9. Macci D., Boni A., Cecco M., Petri D., *Multisensor Data Fusion*. "IEEE Instrumentation and Measurement Magazine", Part 14, 2008, 24–33.
10. Kropas-Hughes C.V., *Data fusion for NDT: what, where, why and how*. "Materials Evaluation", Vol. 61, No. 10, 2003, 1118–1120.
11. Chady T., Psuj G., Lopato P., *Data fusion of eddy current NDT signals*. "AIP Conference Proceedings, Golden", CO, 2008, 610–617.
12. Quintino L., Liskevich O., Vilarinho L., Scotti A., *Heat input in full penetration welds in gas metal arc welding* (*GMAW*). "The International Journal of Advanced Manufacturing Technology", 2013, DOI: 10.1007/s00170-013-4862-8.

Zastosowanie fuzji danych dla potrzeb diagnozowania procesu spawania

Streszczenie: Spawanie łukowe jest powszechnie stosowane w przemyśle. Ocena jakości połączeń spawanych jest jednym z najważniejszych zadań, zwłaszcza w przypadku produkcji wielkoseryjnej na stanowiskach zautomatyzowanych. Parametry spawania, takie jak prąd, napięcie itp., są bardzo często stosowane w diagnostyce procesu spawania. Rozpatrywanie pojedynczych sygnałów w ocenie procesu spawania nie jest jednak zawsze skuteczne gdyż informacje diagnostyczne zawarte w sygnałach procesowych wzajemnie sie uzupełniają. W artykule przedstawiono badania poświęcone użyciu technik fuzji danych w diagnostyce procesu spawania. Zastosowano metody fuzji działające na poziomie sygnału oraz decyzji. Wyniki badań potwierdzają, że proponowane podejście ma potencjał do dalszego stosowania.

Słowa kluczowe: spawanie, diagnostyka procesów, analiza sygnałów, fuzja danych

Artykuł recenzowany, nadesłany 24.06.2013 r., przyjęty do druku 13.11.2013 r.

Marek Fidali, PhD Eng.

Assistant professor in the Institute of Fundamentals of Machinery Design at the Faculty of Mechanical Engineering of the Silesian University of Technology. He received the Master of Science and PhD degrees in Mechanical Engineering from Silesian University of Technology in 1997 and 2003, respectively. His research interests lie in technical diagnostics in the broad sense, infrared thermography, images and signals processing methods as well as modal analysis, measurement systems and acoustics.

e-mail: marek.fidali@polsl.pl

Wojciech Jamrozik, PhD Eng.

Assistant professor in the Institute of Fundamentals of Machinery Design at the Faculty of Mechanical Engineering of the Silesian University of Technology. He received the PhD degree in Mechanical Engineering from Silesian University of Technology in 2012. His main research areas are technical diagnostics, image processing and analysis, as well as aggregation of incomplete and uncertain information in technical diagnostics.

e-mail: wojciech.jamrozik@polsl.pl