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PHOTO GRAMETRY BASED WELDING QUALITY ANALYSIS FOR SEMI AUTOMATIC WELDING MACHINE

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ABSTRACT

The work presents a new method capable of identifying the welding defects using signature image processing (SIP) techniques, which includes the radon transformation, edge detection, photogrammetric and the morphological mathematical operators. Signature Image Processing (SIP) is a technology for analyzing electrical data collected from welding processes—usually automated, robotic welding. It is one of the reliable non-destructive testing techniques for weld inspection. This process gives the quality appraisal of a scanned weld, detailing the location and the geometry of all detected flaws. The image of welding is taken using a DSLR (Double Single Lens Resolution) camera in RAW format .A digital SLR camera was used to photograph the test plate's surface shape using a multi station convergent network. The RAW image is then converted to uncompressed TIFF format image. This image is analysis to find the defect by using the radon transformation and the MATLAB. These samples have included the simple butt joints and following the sample welding plates were used to determine the defects in it. This system is available to the quality control of butt joint and used to estimate the welding strength and detect the defect. Mat lab was used to interpolate the target coordinates into a regular grid and to detect the defect in the welded pieces. Initially the processing is done by mat lab with image processing tools and it is required to find the defect detection and subsequent sizing and positioning.

Keywords: DSLR, MATLAB (image processing tool).

INTRODUCTION

The aim of the project is to check whether the quality of welding is good or bad, it has been checked continuously by means of the image processing techniques. The technique is the data from an image are digitized, and various mathematical operations are applied to the data, and the digitize images are observed and finding the quality of welding. And it also called as picture processing. Using this technology we are reducing considerably the total amount of time needed for quality checking, at the same time the number of inspected components is increased. This image acquisition and post-processing are very useful in real time application. The need of this application is to identify and measure the main quality of welding. And the welding quality is monitor every time and the all faults are detected by the process of signature image processing method; in this method we are using the radon transformation techniques. By which the fault are corrected continuously and effectively. It is a technology used to analyze the electrical data collected through a welding process. Certain conditions are necessary for welding to be acceptable and little variation in it can become the cause of rejection. There was a need of a reliable system that could detect welding fault in real time. SIP is a system that can identify the smallest of faults in the welding process. The use of SIP has increased significantly in the automotive industry and it has resulted in the improved quality of welding.

This quality checking has been done by the method of photogrammetric, radon transformation and signature image processing. By combining these methods the quality of the welding faults are identified.

EXPERIMENTAL

Signature Image processing: By using these algorithms to assess the quality of the welds products and faults occur in welding arcs. The critical realization was that a way of determining the quality of a weld could be developed without a definitive understanding of signature image processing. The development involved a number of advances. The first was a method for handling sampled data blocks by treating them as phase-space portrait signatures with appropriate image processing. Typically, one second's worth of sampled welding voltage and current data are collected from GMAW pulse or short arc welding processes. The data is converted to a 2D histogram, and signal-processing operations such as image smoothing are performed. The second advance was a technique for analyzing welding signatures based on statistical methods from the social sciences, such as principal component analysis. The relationship between the welding voltage and the current reflects the state of the welding process, and this information is contained in the signature image.

Comparing signatures quantitatively using principal component analysis allows for the spread of signature images, enabling faults to be detected and identified. The system includes algorithms and mathematics appropriate for real-time welding analysis on personal computers, and the multidimensional optimization of fault-detection performance using experimental welding data. Comparing signature images from moment to moment in a weld provides a useful estimate of how stable the welding process is. "Through-the-arc" sensing, by comparing signature images when the physical parameters of the process change, leads to quantitative estimates for example of the position of the weld bead. Data blocks of 4,000 points of electrical data are collected four times a second and

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converted to signature images. After image processing operations, statistical analyses of the signatures provide quantitative assessment of the welding process, revealing its stability and reproducibility, and providing fault detection and process diagnostics.

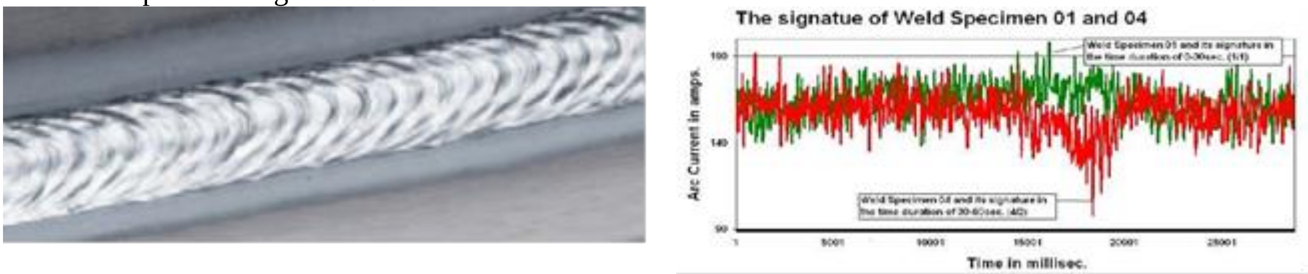


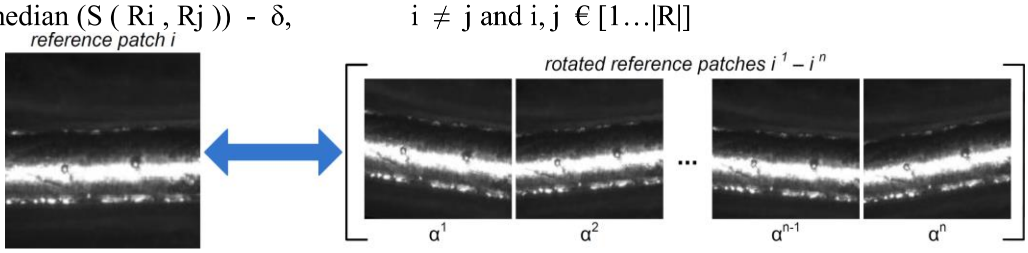
Fig.1.Example of Signature Image Processing

RESULT

Defect Detection: In continuous industrial use, each unseen image patch is compared to the reference data entries by evaluation of a similarity measure. Image patches that exhibit high dissimilarities are rated as unusual events. Classification of patches p into error-free or defective is given by the computed similarity values sp, respectively. If sp falls below a process specific detection threshold _, p is classified as defective. Basically, any similarity metric S: R^2 * R^2 R, which allows a pair wise comparison of image patches, can be applied. We chose the two-dimensional normalized cross correlation (NCC), which is commonly used in computer vision for template matching. It is simple, fast, and more robust to lighting changes, compared to e.g. the sum of squared differences (SSD).

We perform robust matching by applying a rotating and sliding window approach as depict in below figure. Reference image patches are rotated by α^i and cropped to overcome slightly translational and rotational misalignments during image acquisition, resulting in more robust matching. Scale variations could be considered by a scale-space oriented approach, but as camera and welding machine are rigidly connected, resulting in a constant working distance for the complete welding process, this is not necessary in our case. During welding each newly acquired image patch p is assigned a similarity sp to clustered reference data. All patches with a similarity value s_p smaller than a process-specific detection threshold θ are reported as unusual events, and consequently as potential welding defects. We determine θ from available reference sequences R in a way, that a welding sequence can be classified either into error free or erroneous without any further information or learning efforts. We used the median as well as a safety margin θ, which was set to 0:09 b= 9% within our experiments, to be robust against potential outliers:

$$\Theta = \text{median}\left(S\left(R_i, R_j\right)\right) - \delta, \qquad i \neq j \text{ and } i, j \in [1\ldots|R|]$$



Welding quality inspection: Application A separates complete welding sequences into either error-free or defective ones. We show that a single unusual event suffices to classify the corresponding sequence as defective. Application B exactly locates punctual defects on the welded seam. This application is of interest for welding tasks, where small punctual defects might be tolerated considering quality inspection. We evaluate our method on 9 different welding process datasets. The corresponding sequences are characterized by extreme illumination changes, heavy smoke, spatter and spilling, curved welding, different welding speeds, and different materials. In this way, we demonstrate that our method can cope with the high variability and noise of industrial welding processes. To allow a quantitative analysis of welding defects, evaluated welding sequences as well as corresponding image patches have been manually classified into error-free and defective by an expert. Each welding process dataset consists of 11 error-free and 9 erroneous welding sequences. Evaluated sequences contain between 103 and 231 image patches of size 161 * 161 px. Erroneous welding sequences show typical welding errors like holes, narrow weld seam regions, blisters, deformations, or gaps. Four out of ten error-free sequences are chosen for reference data generation.

The remaining sequences are used for method evaluations. Overall, 153 welding sequences consisting of a total of 25166 welding image patches are evaluated. Considering run-time, our Matlab implementation of the proposed method reached an average processing rate of 51:20fps on an Intel Core i7 2:8 GHz processor. Hence, real-time processing at typical image acquisition rates of 10 □ 20fps is definitely feasible.

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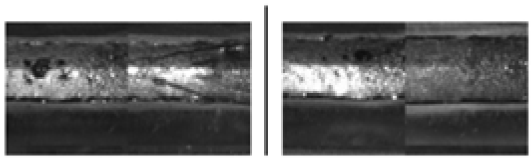
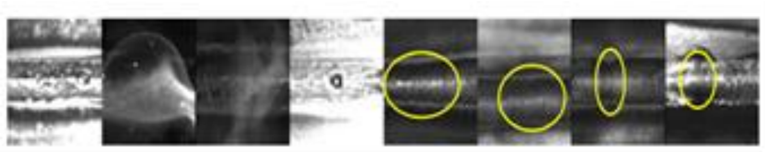
Sequence Classification

The goal is to classify complete welding sequences into either defective or error-free, regardless of the type of error that occurred. As soon as a single similarity value exceeds the reference threshold θ , the sequence is classified as defective. In below figure the number of unusual events is shown over varying similarity thresholds for a sample welding process. The reference threshold θ and the ideal threshold are marked, where ideal denotes that no unusual events are detected within error-free welding. The marked distance d for the reference threshold θ illustrates, that a desired separation of error-free and defective welding is feasible. Our experimental evaluations show that 0:09 b= 9% is a reliable value for θ for the reference threshold computation, as an average classification accuracy of 93% has been achieved.

Defect Localization: Considering e.g. welding on the base plate of cars, very long sequences might be welded. Here, discarding of objects with small punctual welding defects can be unnecessary and costly. Knowledge on the exact location of welding defects provides the option of e.g. automatic repair or targeted manual inspection afterwards. Due to the availability of ground truth data, provided by an expert, true positives (correct defect detections), false positives (incorrect defect detections), true negatives (correct error-free detections), and false negatives (incorrect error free detections) are evaluated for each welding sequence, respectively. Examples of correctly detected welding defects as well as error-free image patches from welding process with ID 4 are shown in below figure.





Samples for Remaining Problematic Welding Patches: Databases typically consist of 10 □ 20 cluster centers. This results in reduced costs for reference data generation, and in real-time capability. Industrial applications usually require a high degree of robustness and real-time performance. Experimental results empirically show that a separation of welding sequences into defective and error-free welding is feasible, accurate, and fast. Furthermore, localization of welding defects is possible due to incorporation of information on the robot motion. Considering the amount of reference data used for our initialization step, more training sequences would result in more accurate welding process models, which allow detection of welding defects at a finer level. The detection of slight contractions considering weld seam width is not feasible with only four reference sequences. We also observed that the chosen similarity metric (NCC) cannot cope with severe illumination and intensity variations caused by e.g. gas disturbances. Future work will address the classification of problematic image patches, exploitation of the present redundancy, and incorporation of additional measures like the seam width and shape.

Prior to polarization, the open circuit potential was around -770 inVA,. Images shown in below Figure a and b were recorded at -864, and -819 inVA, close to the start of the potential ramping, On visual observation there are no dissemble differences. However, digital subtraction of image b from a resulted in the difference image shown in below figure, where corrosion sites are clearly located. They appear as white spots with some showing comet-like tails due to pH indicator changes. All the tails were in the same direction and resulted from solution convection, which is generally seen even in the confined volume of the 25 in container. In contrast to the gray scale in Figure IC, the original color of the difference image showed the comet tails were green close to the spots and changed to red with distance from the corrosion site. The amount and hue of the color change is a function of the subtraction parameters and the times the real images were taken. The red color was due to a decrease in pH to <4, the lower limit of the pH indicator. The green was produced by the first image having higher red intensities than the same areas in the second image, so the result of subtraction is a lower red intensity in the difference image, which is perceived by the human eye as a green color. It should be noted that the color of the difference image represents relative changes in pH as a function of time, rather than absolute values of pH. The green color of the tails became the white color shown in the figure when the image was converted to a grey scale representation for publication.

The below figure shows, a difference image taken during the third scan. Here the first image was taken before the anodic current had increased, the second while the anodic current was increasing. When corrosion was in progress tlie sites were very dark, possibly due to diffraction of light in the concentrated solution around the sites. When corrosion stopped, the sites were longer dark. At times bubbles coming from the site also appear dark, but these were initiated occurrences. Additional processing of this image showed pH changes around the corrosion sites associated with a limited period of diffusion. Here the difference image showed the site as dark spots in contrast to that seen below. Hence the white or dark spots offer a way to determine the chronology of the different corrosion sites even without the addition of a pH indicator.

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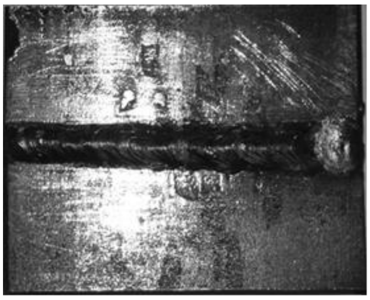
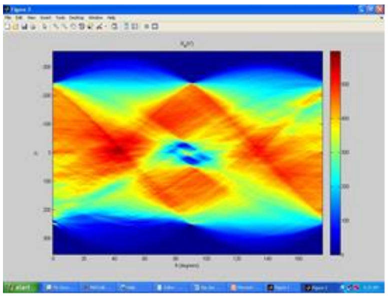
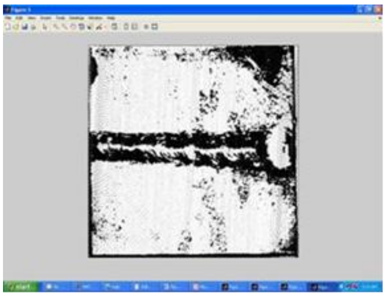
The above analysis demonstrates a number of different inductions of sites of corrosion. Circles in Figure b have marked the indicated sites of corrosion taken from Figure c. One site is clearly above a taped area. The cause of this indication is not known for certain. It could have been due to crevice corrosion penetrating under the coating, but post exposure examining of the sample showed no evidence of crevice corrosion under the tape. Another possibility was the presence of a particle floating in the solution. The movement of these particles is often seen in the solutions and care must be taken to eliminate all particulates within the solution, on the sample, or on other components in contact with the solution.



Original image Good welding

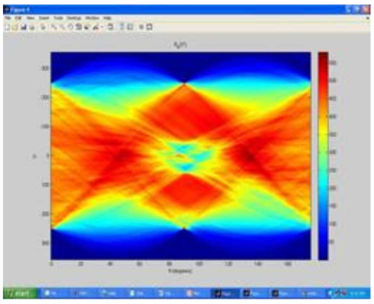


Radon transformation output Good welding

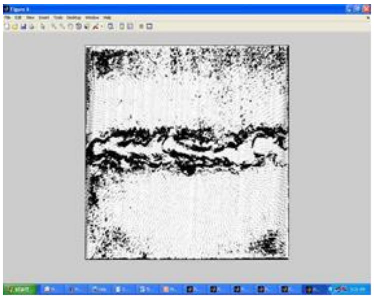


Inverse Radon image Good welding

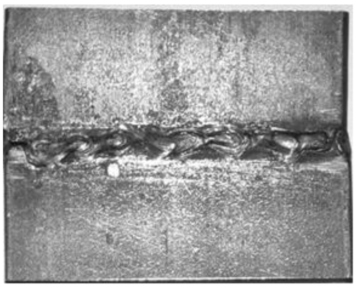
Original image medium welding



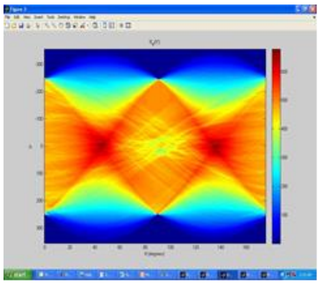
Radon transformation output medium welding



Inverse Radon image medium welding



Original image worst welding



Radon transformation output worst welding

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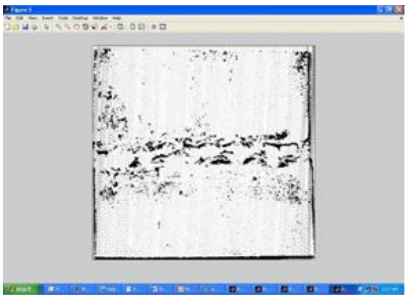

Inverse Radon image

CONCLUSION

This project has addressed the task of positioning of defects in image processing. An image processing technique has been developed to overcome the welding defects and their associated errors, resulting in a batch weld appraisal system where defects are automatically detected and positioned. This would make the proposed system suitable for implementations in situations requiring near real-time processing and interpretation of large Welding images, and thus these techniques are expected to greatly reduce the possibility of human and experimental error, due to loss of concentration and visual fatigue.

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