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Abstract: The development of new approaches in image processing and retrieval provides several opportunities in supporting in different domains. The group of welding engineers frequently needs to conduct visual inspections to assess the quality of weldings. It is investigated, if this process can be supported by different kinds of software. A generic CBIR system has been successfully used to sort welding photographs according to the severity of visual faults. Similar algorithms were used to automatically spot and measure the diameter of gas pores.
Keywords: image analysis, content-based image retrieval, repository, welding defects, surface analysis

1. Introduction

Image retrieval is always challenging in computer science and other disciplinary applications [4]. Advanced image retrieval techniques are largely deployed in medical science, building industry, airplane industry, etc. [11, 2, 9] and also adopted in other domains, such as 3D model retrieval [7]. El-Kwae et al developed a Content based image retrieval (CBIR) system in picture archiving and communication system. Ribaric et al used the techniques of fusion of information to extract building images [11]. Cao et al used the methods of linear least-squares (LLS) randomized Hough transform (RHT) for retrieving satellite images [2]. However, these techniques of image retrieval are rarely applied into mechanical engineering, particular in the field of welding.

It has been known that in welding industry, non destructive testing could produce a huge amount of images in the forms of photos, digital images or X-ray pictures containing different types of welding defects which are vital for the quality of industrial products. According to definitions defined by ISO 6520, there are 80 types listed in the documents. For each type, the defects could be grouped or classified into different degrees of severity. It follows that research into developing an advanced system for retrieving, analyzing, classifying and recognizing welding defects is of interest in both academic study and industrial applications. Several current approaches have been described by da Silva and Mery [3].

Much research is undertaken in the artificial intelligence to automatically classify sample images and detect defects in work pieces. A review about non-destructive testing has recently been published by Yella et al. [12]. The areas covered are machine vision, neural networks, case-based reasoning, expert systems, fuzzy logic and genetic algorithms.

Another related area is the object recognition, which can be used to spot common objects on images [5]. This task is required to achieve a fully automatic processing. After spotting the objects involved, weld seams or other regions of interest can be examined by specific algorithms in detail without getting distracted by meaningless background.

The objective of this research is to enrich a generic image retrieval system to achieve retrieving, analyzing and classifying welding images efficiently and accurately. It is tried to add a intermediate layer in between human analysis and artificial intelligence. The proposed approach can be applied to support human decisions without putting much effort into complex machine learning tasks, especially to support trainees in learning to spot defects.

2. Methods employed

In this investigation, the key methods and mechanisms involved are CBIR. Meanwhile, ISO 6520 (Classification of geometric imperfections in metallic materials) is used as supporting document to distinguish different types of welding defects.

Content Based Image retrieval is a technique which can retrieve a large collection of images based on their features, such as texture, colour and shape. To achieve this process, images are normally stored in the image repository. In this investigation a database management system is built up. The latest development in CBIR is to achieve filling a gap between micro-level's pixel graphic contents and macro-level's image meanings, i.e. semantic retrieval [8, 7, 9].

Perner [10] describes a domain independent image database, extracting objects and scenes from the images. Each object is described by a set of features and multiple objects are spatially arranged in a scene. Queries can be either textual or by image.

Based on the basic CBIR mechanisms [10, 8], the architecture of the system is designed. It is in three levels: abstract, generic and specific (fig. 1). It is clear that the system is simple, generic and dynamic. This research takes advantage of the flexible design and domain specific features are developed. Those features may be either very simple or introduce complex pattern recognition algorithms. Two possible features are described below: a measure based on very dark areas in the image and a pattern recognition algorithm to extract the location and size of gas pores in a welding.

Digital images of welding samples can be stored in the resulting repository, and retrieved for visualization and assessment. These images can be at least partially manually annotated with definitions in the ISO classification. This information can then be used for machine learning algorithms or to quickly sort un-annotated images according to the domain specific features and by providing a reference image.

3. Consideration of system design

The semantic gap between the pixels and the semantics cannot be completely closed with current technology. Thus, the intended software is developed in several steps with methods specific for the given application domain.

In the first stage, a previously developed CBIR system [8] is used. This system is allowed to define a single query containing different image features as well as textual meta information. The features previously implemented for the system are focused on a general visual similarity, such as histograms and colour distributions. Due to the open design, it is possible to add domain specific plug-ins to the retrieval engine, in this case to capture different kinds of welding defects.

Due to the wide range of possible fault types in an image, it is necessary to develop a specific algorithm for each fault. While it is not expected to return perfectly reliable results, the automatic analysis can already give some direct feedback. This can help engineers to spot the faults or to quickly retrieve similar samples from previous work. In order to gain high-quality results, existing recognition algorithms may also be added.

3.1 Implementation

One feature developed in this system is that the software can carry out a straight forward analysis of the darkest areas in the sample images. Depending on the lighting, cracks and inclusions can be spotted by searching for dark areas. Comparing the qualities with a good and a poor sample, for the same type of the two work pieces, the software allows for a quantitative comparison. It is assumed that a defective sample exhibits more conspicuous areas in the poor one than that in the good one. This approach is used to sort a set of kindred samples according to their "faultiness".

The simple feature converts the image into 256 tone grey scale for further processing. The percentage pc is determined by counting the amount of pixels below a threshold (e.g. 50) and calculating the relation between the amount of black pixels n_b and all image pixels n_a:

$$pc = \frac{n_b}{n_a} \tag{1}$$

The threshold between the dark and bright pixels is determined with the help of a histogram that contains bins for each brightness level x_i. The threshold th is the smallest value, where 1% of all pixels are darker:

$$th : \left(\frac{1}{n_a} * \sum_{i=0}^{th} x_i \right) > 0.01 \tag{2}$$

For the comparison of two images, the two parameters of the images (A, B) are used to calculate the similarity s_{AB}, which is a normalized value between 0 and 1. The difference between the parameters of each image is calculated and normalized. The normalised values are th_{AB} (Equ. 3) and pc_{AB} (Equ. 4).

$$th_{AB} = \frac{\|th_A - th_B\|}{256} \tag{3}$$

$$pc_{AB} = \|pc_A - pc_B\| \tag{4}$$

The overall similarity s_{AB} is constructed as the weighted sum of th_{AB} and pc_{AB}. Currently, both features are equally weighted with $\frac{1}{2}$. As the intermediate result is 0 for identity, it is subtracted from 1. In order to emphasize differences, the result is squared.

$$s_{AB} = \left(1 - \left(\frac{1}{2} th_{AB} + \frac{1}{2} pc_{AB}\right)\right)^2 \tag{5}$$

The brightness threshold already indicates some suspicious areas in an image. Those areas can be analyzed in a more sophisticated way by assuming certain fault types. For each one an algorithm can be used to measure characteristics. Example are the determination of the length and orientation of cracks or the size and location of inclusions.

The second feature vector measures the diameter and location of gaseous inclusions. The original image is pre-processed in several steps in order to reduce the background noise and to extract the desired information easily. The detection uses two different approaches in parallel. The first one is used to mark all regions of interest, which are represented by black pixels. The pattern recognition algorithms only need to work in those areas.

1. Median filtering to remove "salt and pepper" noise
2. Conversion to grey-scale by brightness
3. Conversion to bi-level image with a given threshold
4. Removing single pixels that are considered to be noise by dilation and erosion

The second approach performs an edge detection to emphasize the location and shape of structures in the resulting image. This information can be used to match possible shapes that are retrieved in the previous step.

1. Median filtering to remove "salt and pepper" noise
2. Edge detection

By applying a Hough transform [1] for filled circles on the first image, a set of potential inclusion candidates can be generated. Each potential circle encloses several black pixels. A first estimate of the relative matching quality can be calculated by $m = \frac{relevant\ pixels}{\pi * r^2}$. Circles enclosing a too small amount of relevant pixels can be removed from the results, as the shape is probably too different. To confirm the location of each circular defect, the second image containing the edges is used. Assuming, the detected circle is correct, it should match the detected edges. If this is not the case, other solutions have to be checked. The resulting data tuples for each circle contain position of the centre (x, y), radius r and the match m. Each feature vector describing a single image is a list of those tuples. A perfect

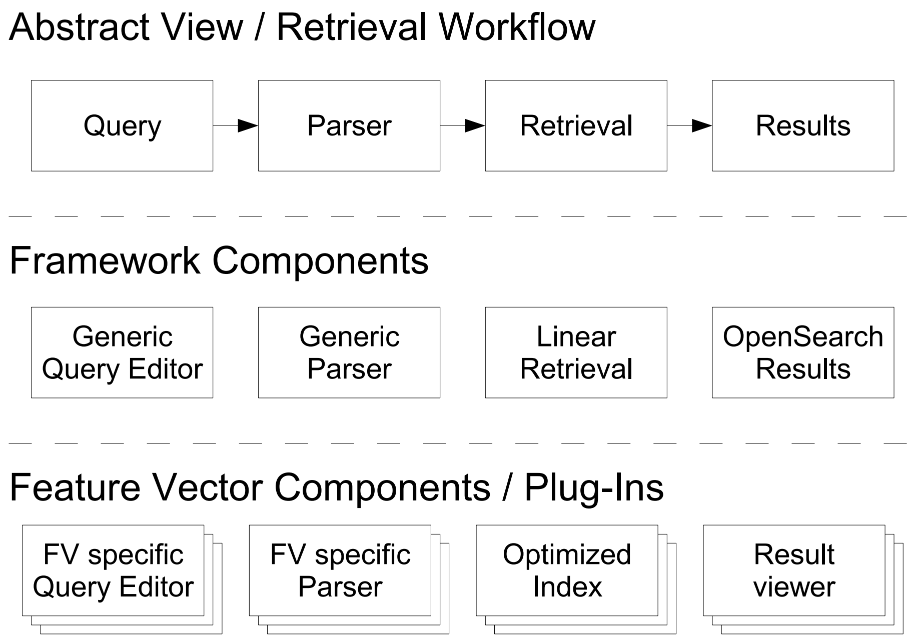


Fig. 1. Layered System Design

sample is expected to have no entries at all. These lists describe the faultiness according to gas porosity and especially amount and size of pores can be used for sorting.

The recognized defects can be directly highlighted on the image, including information about the diameter and the relative confidence. In addition, this information can also be stored in the repository. Based on the amount, size and location of defects, the retrieval engine is capable of comparing the porosity of each two samples provided.

3.2 Testing

To assess the theoretical assumptions, a couple of tests have been carried out. The first part is focused on the low-level feature and its fault-spotting abilities in a CBIR environment. The second part is dedicated to a more sophisticated detail analysis, e.g. spotting spherical gas pores (2011 ff) according to ISO 6520.

The initial series of images are digital photographs taken by a common camera. Those images show different welding defects compared with error less samples. As visual light is used in those images, it is only possible to analyse the surface of the work pieces. Hence, several defects can be spotted directly or by removing the surface layer in destructive testing.

In order to test the efficiency of the low-level feature, a set of images with similar material are chosen. The repository contains a couple of similar material samples. The surface is gray, rippled and slightly dirty. The overall impression is a gray background with a pattern of darker spots. The faulty samples contain cracks in the surface. One non-defective image is manually chosen to provide a reference of a normal condition. The retrieval system is then expected to sort the corresponding sample images according to their relative faultiness. The more a sample deviates from the "best" condition, the similarity is expected to drop accordingly.

The test set contains two original images with one perfect and one faulty sample. The latter one shows four small cracks on the left hand side. From both images, four smaller images are cropped from the corners to have a testing set of 10 images. The sub images of the intact sample also bear no defects. As the cracks in the second image are located on the left, only 2 images show cracks. Due to the cropping, these cracks take over relatively more space than in the original one, i.e. the faults appear more serious. It is expected that the intact images gain high ranks, while the defective ones end up with a lower rank. The order of defective images should also represent the relative severity of each fault.

The second proposed feature is based on a complex patten recognition task. The amount of sample images containing gas pores is too small to create a reasonable ranking. For that reason the testing effort is focused on the efficiency of the circle extraction algorithm. Each sample image is being processed by the algorithm and the amount and diameter of the extracted defects is checked manually. Images of intact samples should not contain any detected pores, while all of the defects in the compared image should be spotted automatically.

4. Results

Figure 2 shows one example of fault related sorting of images. For the sorting, the "perfect" sample is used as the query image, which appears on the highest rank of the search result. Then the results gradually differ more and more from this sample and gain a lower rank. In figure 2, the images bearing the highest amount of cracks are positioned at the lower end of the list. This ranking did not require any sophisticated machine understanding of the samples and is solely achieved by extracting the relevant feature and using it in a non domain specific CBIR search engine. The relevance score for the images is slightly lower than originally, as a keyword search is merged into the

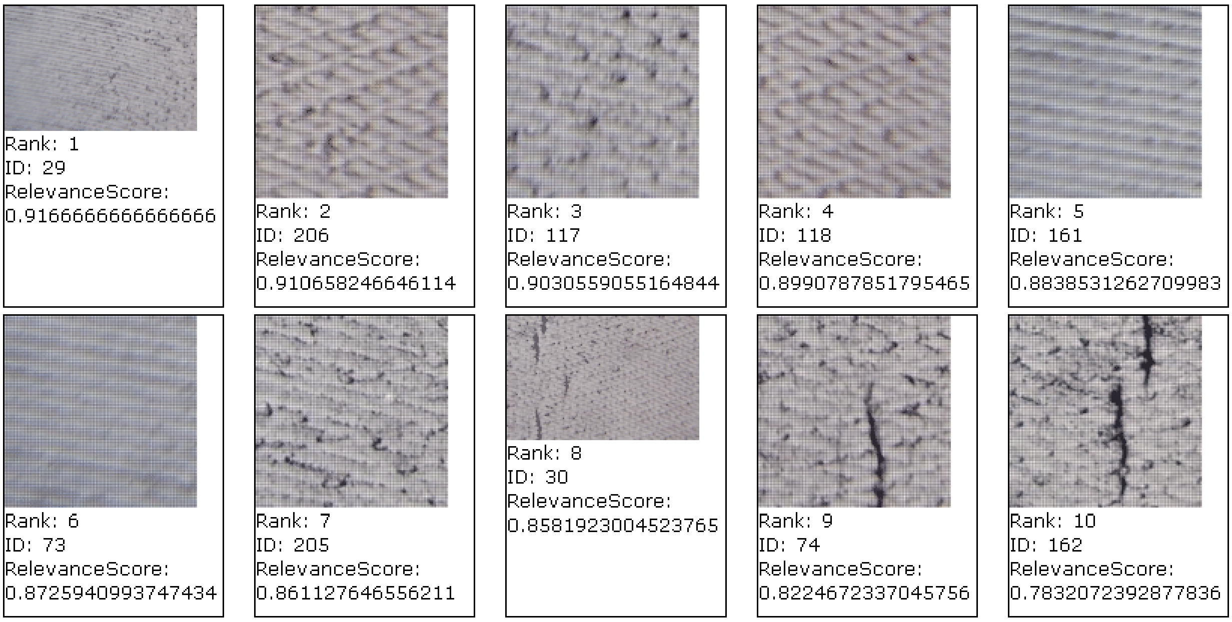
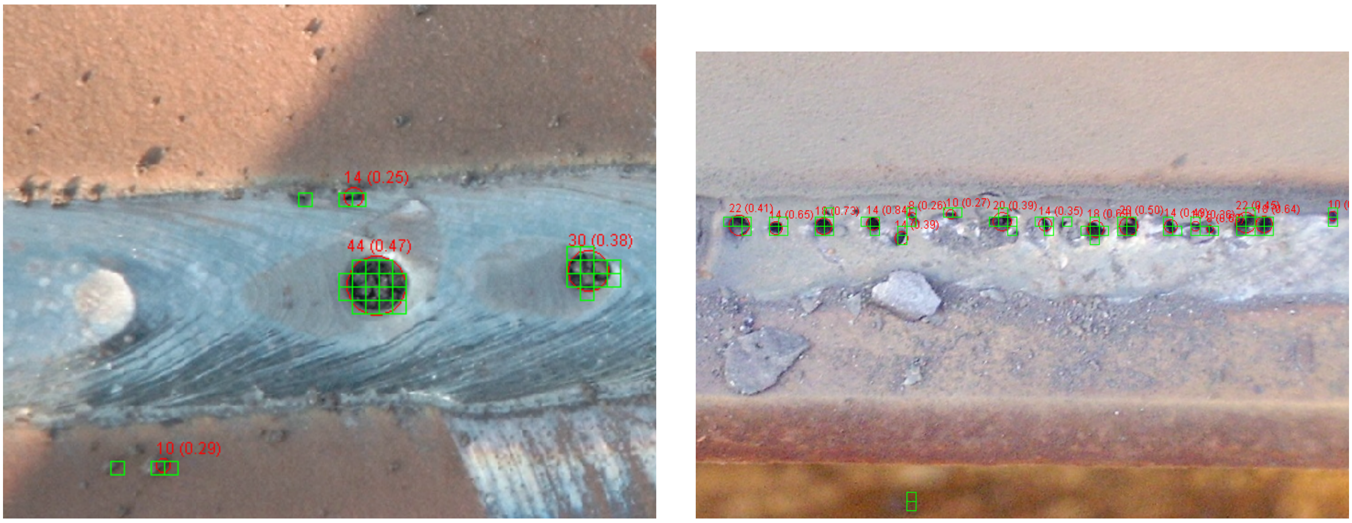


Fig. 2. CBIR search with specialized feature



(a) (b)

Fig. 3. Detection of gas pores

retrieval to filter out unrelated images completely. The amount of reduction is the same in all cases, thus causing no changes of the ranking itself. The first 7 images show intact samples with a slightly irregular surface. Image 8 is the defective original with 4 small cracks on the left. Image 9 shows one prominent crack and the final one two of them.

In fig. 3, the images 3(a) and 3(b) show examples of the pattern recognition task. This analysis uses parts of the previous feature to spot conspicuous areas in each image. The detected gas pores are highlighted by a red circle, also annotated by the diameter (in pixels) and the relative match. The green boxes indicate the regions-of-interest where the algorithm applied the Hough transform.

Figure 3(a) shows a welding seam with three major gas pores and some impurities and smaller defects in the surrounding area. The diameter of the two pores on the right hand side has been determined correctly (match: 47% and 38%). The pore on the left side could not be retrieved, as the lighting in that area is different, causing a bright spot at the location of the pore. Above the centre, a small defect with a more lengthy shape has also been spotted. The calculated match of it is 25%. Below the seam, some dirt casts a dark shadow that is also itnerpreted as defect. Two other areas have been marked as region-of-interest, as there are shadows or tiny defects where no matching circle could be found. In the corresponding “good” sample, no defects were found.

Figure 3(b) depicts another welding with several small gas pores in a line. A couple of chunks have not been cleaned away from the sample and the gas pores are not perfectly round. All pores are spotted and most of them are measured correctly with the smallest enclosing circle. In a few cases, the algorithm merged multiple adjacent pores into a single hit with a higher diameter. As before, no defects have been extracted from the corresponding defect-less sample.

Table 1. Position, radius and match (%) of gas pores (a)

X	278	436	261	119
Y	209	198	143	343
radius	22	15	7	5
match	47	38	25	29

Table 2. Position, radius and match (%) of gas pores (b)

X	47	600	334	472	139	436	620	87	193	224	381	518	278	545	695	236	561
Y	189	186	185	190	190	193	188	192	187	203	188	190	177	190	177	179	193
radius	11	11	10	10	9	9	9	7	7	7	7	7	5	5	5	4	4
match	41	45	39	50	64	69	73	65	85	39	35	49	27	36	43	26	68

5. Analysis and discussion

The first test case is based on common CBIR technology and a simple feature to spot dark areas in the image. No detailed analysis or machine learning was required to achieve the sorted output (fig. 2). The ranking is as expected. The use of a sample image tells the system something about the expected feature parameters and thus defines the perfect sample for a given material. In the other test cases, the results were also sorted with respect to the overall faultiness, independent from the material used. Hence, a drawback of this approach is the lack of comparability between different materials or welding techniques. The ranking also does not contain any information about the nature of defect.

The second test case stands for the development of a domain specific feature vector module that can be integrated in a retrieval engine. The experimental system manages to spot most of the gas pores correctly and accurately. The extracted feature can be used to create an overlay on the original image. The numbers denote the diameter (in pixels) of each circle and the relative match. Those values are listed in tables 1 and 2. Judging the results manually, most gas pores have been spotted and measured correctly. Minor errors occur due to the inconsistent lighting of the surface and the irregular shape of some regions.

The extracted circular shapes contain information about a specific type of defect. The amount of defects indicates the porosity of the sample. The diameter and position of each pore can also help to classify the defect class (i.e. a single pore, a line of pores, etc.). This information is also independent from the material used. Thus, welding samples of different types can be directly compared according to the defect.

In the future, the same analysis will be carried out on x-ray images. In addition that approach allows for completely non-destructive testing. The main challenge is to analyze the 3-dimensional nature of the work piece to be analyzed. However, if several faults overlap it is very likely that several layers of correct material can be interpreted in the wrong way.

In any case, taking original photos and digitalized pictures with a high quality is essential to the successful use of the software. The inhomogeneous lighting conditions in figure 3(a) causes the extraction algorithm to completely ignore one defect. Taking detailed conditions of a photograph into consideration (e.g. lighting, material) may also be helpful to automatically determine the parameters for the extraction of defects.

6. Conclusion and future work

Present work demonstrates that it is feasible to use software in some fault detection for welding industry. A careful selection of features allows the use of standard CBIR algorithms without the need of a deeper machine understanding. The precondition is to select a set of homogeneous samples, i.e. the same base materials and the same welding techniques applied. Otherwise, the algorithms may be distracted.

Analyzing gas pores is one specialized algorithm to spot specific defects as specified in ISO 6520. The analysis can be focused on many other features, such as the size and shape of welding beads. The results may be used to support the untrained eye or to pre-classify a large amount of samples.

To achieve semantic retrieving images from the system, XML technology is well known to be used to describe electronic contents semantically. Thus, integrating XML into part of future investigation is necessary [6]. A set of images will be correctly annotated by specialists (e.g. type of welding, extent of defect, ISO defect class) in a ground truth database. It can then be used to assess new images.

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