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ScienceDirect
Procedia Engineering 69 (2014) 518 – 525
Procedia Engineering
www.elsevier.com/locate/procedia

24th DAAAM International Symposium on Intelligent Manufacturing and Automation, 2013

Visual Measurement of Material Segregation in Steel Wires

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Abstract

In this article we introduce a visual measurement system intended for an automatic determination of material segregation in steel wires as a feedback quality control. Our system is based on an image processing which represents a non-destructive field in measurement area. Until our automated inspection system has been deployed, the measurement of segregation level was accomplished by a human inspector who represents inexact and subjective evaluation. Moreover our automated classification of individual steel wires is based on a certified official regulation. The mentioned automated classification of wires into pre-defined classes is carried out by a sequence of image processing steps. All these steps are progressively described in this article in-depth.

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Keywords: Automated inspection; image processing; material segregation

1. Introduction

Keywords: Automated inspection; image processing; material segregation; The output inspection is an important process in the steel industry and elsewhere. The inspection of a level of material segregation in steel wires is used as a feedback control for a determining quality of final products. The inspection is done by using of a visual process and accuracy depends on an inspector's subjective a point of view. The inspector compares each sample with a norm and estimates a class of the degrees of material segregation. It is obvious that different inspector may classify same sample to the different class. For this reason all output control may be wrong.

The task of the automatic classification system is to reduce errors to a minimum and getting same results for a long time. The big stress is a repeatability of the measurement. Unfortunately, optic structure of a material surface has an influence to repeating of the measurement. The quantity of carbon in a material is describing this article. An automated process of determining of carbon level in steel wires is described in the following sections.

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Selection and peer-review under responsibility of DAAAM International Vienna
doi:10.1016/j.proeng.2014.03.021

2. Wire analysis

The degrees of segregation are measured in a cast of steel wire. The process of cooling of wire causes condensing of the carbon in the material. After that, according to the quantity and the structure of the carbon in material, the level of the segregation is defined.

The level of segregation is determined based on a table contained in the standard. This table contains four classes (A-D) of segregation and every class has five degrees of severity (UL, ZL, Li, TZ and ZW). Each class has unique style of condensing of carbon and each level of class defines the quantity of the carbon.

Unfortunately, in practice the boundaries between classes are not so sharp, as indicated by the standard. Individual classes are often intertwined and it can be very hard to determine membership to relevant the set [1], [3]. The same problem is in determining level of the class. This problem has to be solved by using a statistical method as it will be shown later.

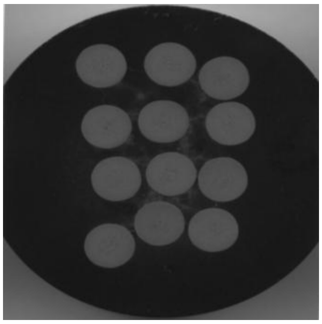
The analyzed wires have a diameter from 2 to 6 mm. A sample for testing can be made by a vertical cutting off a wire. The tested surface is then properly chemically treated. Samples of wires are put into a plastic cylinder for a better manipulation and a faster testing. The number of wires in the plastic cylinder depends on the diameter of wires and is usually between 2 and 12 samples. A plastic cylinder with the six some of wires is on the next figure.

Fig. 1. Clams with six wires.

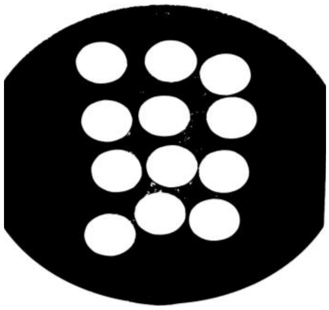
Each position of wire in plastic cylinder has unique index number. This is from reason repeatability of the measurement.

3. Wire analysis – image acquisition

As it was said before a diameter of the wires is very small. It's necessary to scan wires in a high resolution to classify correctly. For this reason it's good to use an ordinary office scanner. Using scanner makes produce images of resolution of 3600 dpi possible. Level of resolution experimentally found 1200 dpi is sufficient. Higher resolution of a dpi didn't bring more useful information. At the moment when the image of the plastic cylinder (clamp) with individual wires it's necessary to separate the wires in the clamp [2]. The scanned image of wires shown on the figure 2. As seen on the figure 2 the individual wires don't have circular neither elliptic shape. Even the wires in the clamp can touch each other that makes segmentation more complicated. K-means algorithm has been chosen as the segmentation method. This algorithm divides the image in to pre-set groups [8], [10].



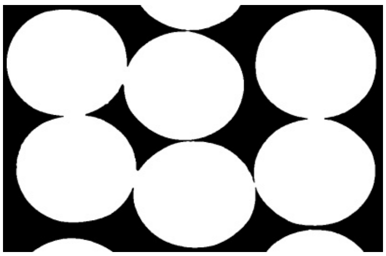
a)



b)

Fig. 2. (a) Scanned clamp; (b) Scanned image after k-means.

After using K-means algorithm the background is separated from the main part of the image. Main part of the image hasn't got only wires, but also dirt and noise. Morphology operations (e.g. binary opening) are used for a noise reduction [7], [14]. The others objects are described by properties. The identification of wires and other objects is based on objects properties [4], [5], [8].



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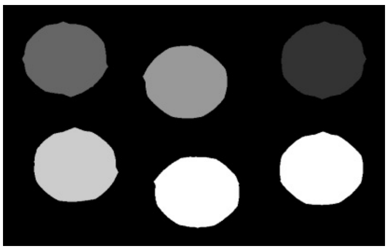

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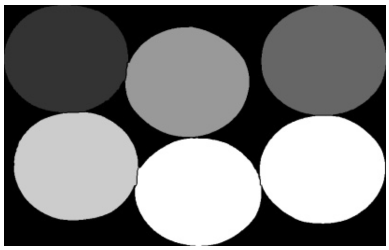

c)

Fig. 3. (a) Connected wires inside a cylinder; (b) Segmentation process of connected wires based on centers detection; (c) Result of connected wires segmentation process.

It's possible that two or more wires touch one each other and it may complicate wire identification. For this reason an operation of detecting touching wires is done before the identification of wires. Touching objects are detected based on big area property that is bigger than statistically common area in pixels of wires [2]. Touch points are deleted and the process of identification continues. Wires indexation is made by putting the position of individual wires to predefined mesh. Every position of mesh has its own index as seen figure 4. After this step degrees of segregation are determined for all wires.

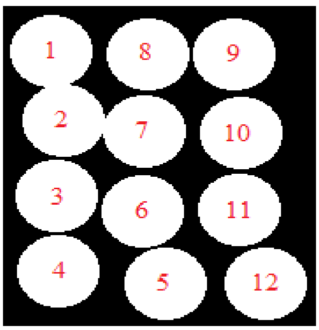

Fig. 4. Key of an indexing.

4. Wire analysis – segregation detection

The level of segregation is determined for all input images like on the following figure 5. During the analyses it was found out that the scanned image has low dispersion of values of brightness [15]. This dispersion has only units of the brightness.

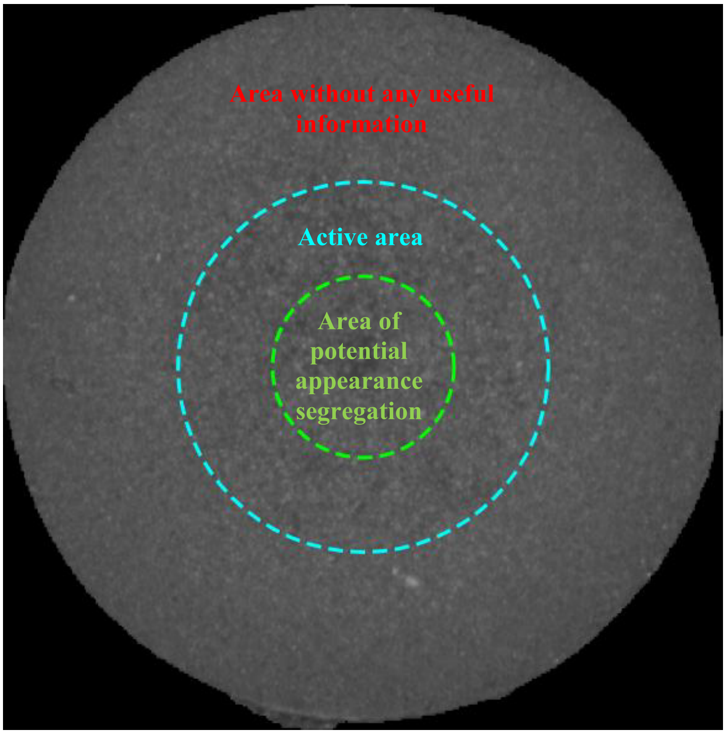

Fig. 5. Three parts of the wire.

This fact makes the classification of segregation more difficult because the information is devalued by noise and surface reflectivity of material. For this reason it was chosen the following process. The first step is to analyze parts of wire area. It was statistically found out that the area of every wire contains a several parts [3], [6].

a) Area of potential appearance segregation
b) Active area of the wire
c) Area without any useful information

The area of potential appearance of segregation is part of the wire where is found precipitated carbon. The radius of this area has been found by experiments for 30 percent of the wire radius (0,3R).

Active area of the wire is a part of wire with important statistic information about a distribution of pixels values in wires. For this reason this part is the referential one. Its size is 60 percent of the radius (0.6R)

The area without any useful information is the border part of the wire. In this area there is a distortion that comes with scanning the clamp. After the separation of area to three parts, the classification of segregation can be started. The process is shown on the diagram in figure 6.

Fig. 6. Flowchart.

The parameter of the mean brightness value μ and the standard deviation σ are determined from the active area [11]. These parameters are used for calculating threshold. The threshold is used for the segmentation of dark carbon elements in the wire [13]. The next formula shows how to calculate the threshold.

$$thr = \mu - params_{thr} \cdot \sigma \quad (1)$$

The parameter $params_{thr}$ is a coefficient of the detection segregation sensitivity. The setting of this value is elementary for the correct results measurement. If the parameter has a high value then sensitivity of the detection segregation is low, but if the parameter has a low value then the algorithm detects wrong regions with segregation. This value has been found statistically from set of measurement. See on chapter 5. Finding properties.

4.1. Determination of WSA parameter

Figure 7 shows found objects after segmentation. All objects aren't the segregation. From this reason the filtration of useless objects is made. Objects are described by properties for identification [4], [12]. Properties are:

- location of center of the mass
- distance center of the object from the center of the wire
- the area of object in pixels
- boundary box

Useless objects can be separated to three classes:

- Noise
- Objects outside of active the part
- Objects with zero standard deviation

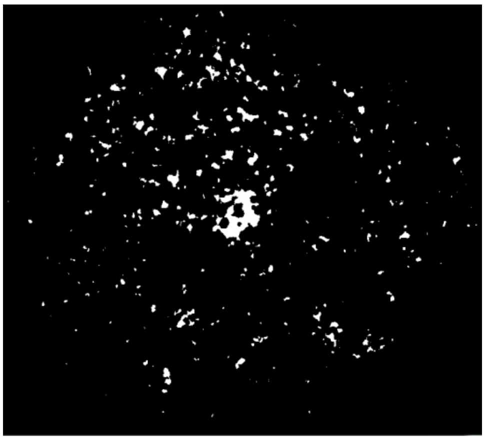

Fig. 7. Product of the thresholding.

After deleting useless objects is computed parameter WSA by using next formula.

$$WSA(A) = \sum_{p \in A} \left(\frac{thr - p}{\sigma}\right)^2 \quad (2)$$

Where p is value of pixel in area A.

WSA parameter is computed for all objects in the image. After computed WSA parameter it is necessary to normalize values by distance from the center of the wire.

$$WSA_{norm} = \frac{WSA}{disttance} \quad (3)$$

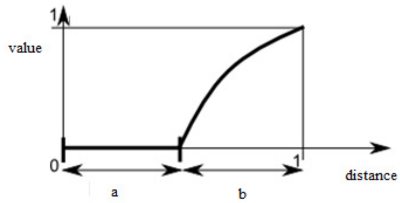

Fig. 8. Distance function.

In this moment all objects have WSA normalized parameter and algorithm finds higher value of this parameter. This object is found as segregation. Level of the segregation is determined by WSA parameter value. Breakpoints values between levels were found statistically.

5. Finding properties

As mentioned above all parameters were found by a statistical analysis. The analysis made for set of data was classified by using a visual method. The sets of data were divided into classes of the segregation. The disadvantage of this classification is that there is no information about level of segregation (percent level of GN, UL, ZL). The table shows the size of the set.

Table 1. Number of the samples.

Class	quantity
GN	520
UL	813
ZL	4
Total	1337

The levels of LI/TZ/ZW aren’t mentioned in the table because these levels don't exist in real. The parameters were extracted only for mentioned classes. Other parameters were extrapolated from known parameters [9]. It's necessary to say that there was a big mistake in a visual classification. The repeatability of the visual classification is low and the accuracy depends on subject view of a controller. The parameters (e.g. WSA) were found by statistic from probability distribution.

6. Conclusion

In this paper the first step of the measurement degree of the segregation was described. The comparison is an important feedback control of the results. The comparison is made by the visual classification and by the repeatability measurement. Surprisingly, a big trouble is caused by measurement repeatability. It is caused by the wire surface. The wire surface is dependent on the falling light direction. When the clamp is scanned for the second time, that final image is little different from the first scanned image. The material of the wire consists of little crystals and this material and condensed carbon reflect light to a different way. For this reason the second image has a different size of area of the carbon and classification algorithm may have wrong results. This situation is shown in the next graph.

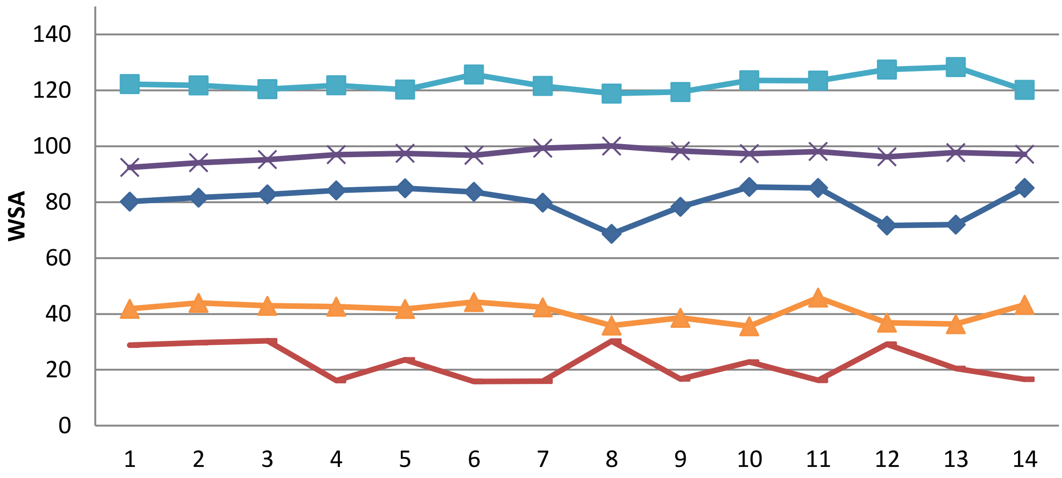

Fig. 9. Stability of the measurement.

The WSA parameters are on the vertical axis and the numbers of the measurement are on the horizontal axis. As graph shows, the crystal material influences results of the WSA. In the rare situation the algorithm may classify results to a wrong segregation class. But the classification is still accurate. The algorithm has a stable level of the repeatability.

Table 2. Coincidence between manually and automatically evaluated samples.

Class	Set 1
GN	70.1 %
UL	68.1 %
ZL	66.7 %
Grand Total	69.0 %

The accuracy of the algorithm was compared with visual inspection [1]. The testing set was different than set for learning. The results of comparing are shown in table 2.

The set for testing has 864 elements. As table 2. shows, the accuracy is still around 69%. The result Grand Total shows weighted mean all tested data. It is necessary said that isn't known real value of testing elements, because visual inspection isn't accurate.

This problem cannot replace different way, because don't exist different complete solutions. Its possible used others methods analysis (textures analyze, frequency analyze, etc.), but this methods aren't stabile as our method. In the future, this method will be stay develop. Hybrid classification methods may be use as good perspective for future work. This field of interest will be tested and some methods already are in developing now. But accuracy of these methods isn't better then described method in this paper for now.

The next different way of increasing accuracy may be understanding principle of a structure of the wire material. Benefits may bring a special filter function that will connect crystals elements together. This way of a research will be tested too.

Acknowledgements

This work was supported by the grant "Research of Modern Methods and Approaches in Automation" from the Internal Grant Agency of Brno University of Technology (grant No. FEKT-S-11-6).

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