International Journal of Advances in Computer Networks and Its Security
Volume 6 : Issue 1 [ISSN 2250-3757]
Publication Date : 18 April, 2016

Image Processing-Based Non-Metallic Inclusion Detection Framework with Extreme Value Distribution

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***Abstract*— Non-metallic inclusions are one of the main problems in steel industry. They are formed by chemical reactions during the steel production process. Non-metallic inclusions have negative effects on mechanical properties of steel. Thus, the detection and the classification of them are very important for the product quality. In this paper, we have developed a sulfide type non-metallic inclusion detection and classification system employing image processing algorithms according to internationally accepted standards. In addition, the system has been analyzed using Gumbel Extreme Value Distributions to predict the expected extreme valued length of inclusion. The system has been tested with AISI 1040 steel as an example, and successful results have been obtained.**

***Keywords*— Image Processing, Non-metallic inclusions, Gumbel, Extreme Value Distribution.**

I. Introduction

Steel is a vital raw material and has extensive usage for the modern-day industry. Due to the industrial revolution and the improvement of technology, a large number of areas including aerospace, automotive, defense industries have started to use steel as a main raw material for production. The clean steel is defined such that it does not contain large inclusions and does not consist of inclusions affecting fatigue strength [1]. Non-metallic inclusions in steel are chemical compounds that occur during the steel manufacturing process. While the steel is melting and pouring, chemical reactions and physical activities cause the formation of non-metallic inclusions [2]. Non-metallic inclusions affect the fatigue strength of steel and cause the failure on the product of steel. [3] Non-metallic inclusions can be grouped in four main types based on the chemical composition. The distinctive features of these types are based on gray level value and their morphological characteristics. The cleanliness of the steel is as important as the quality of the product. Non-metallic inclusions can be found on every steel material more or less. The detection of these non-metallic inclusions before the production of the goods is important and it prevents the waste of money and time. The methods for characterization of non-metallic inclusions have been grouped as the techniques based on surface analysis by optical microscopy, non-destructive testing (ultrasonic test, magnetism-related techniques, X-ray transmission), inclusion concentration methods, chemical analysis, fracture methods, oxygen determination, spark emission, statistical prediction [4].

The JK (Jernkontoret) chart is one of the important studies for inclusion analysis [5]. The chart includes some possible inclusion figures and is based on lookalike comparison. It does not give any distribution and measurement information. American Society for Testing and Materials' (ASTM) E45 standard also take the JK table as reference for the standard procedure using image processing algorithms for the detection of inclusions [6]. It defines feature characteristics of non-metallic inclusions and offers methods for detecting them. There are a few similar international standards including DIN 50602, ISO4967 and SS111116. The main differences between the standards are based on measurement algorithms. There are many other studies and methods in the literature for the detection of non-metallic inclusions. There are studies based on scanning electron microscopy systems [7,8]. In [9], non-metallic inclusion detection automated system has been developed for large area detection with laser induced plasma spectrometry. New methods have been developed to detection of inclusion length range between 5μm to thousands of μm, this study overcomes the specimen preparation stage [10]. Statistical methods also have been used for rating non-metallic inclusions. Statistical extreme value theorem has been studied on non-metallic inclusions [11,12,13,14,15]. Also Generalized Pareto distribution has been studied with non-metallic inclusions [16].

The improvement of steel production industry has reduced the amount of non-metallic inclusions in steel and it also reduced the usability of traditional chart methods. Furthermore, for acceptance of analysis results by international foundations, measurements must be carried out in according to international standards. Detection of non-metallic inclusions by human operator can be damaging and it requires a time consuming process. The similarity of non-metallic inclusion types and sensitive measurements may fail the operator. It may cause inaccurate results and decisions. On the other hand, the automatic inclusion detection systems employing image processing algorithms are fast, accurate and reliable. In this paper we have developed such a system and analyzed the non-metallic inclusions according to international standard ASTM E45. The system also employs Gumbel Extreme Value Distributions for detection and estimating maximum length of expected sulfide type inclusions.

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II. Inclusion Detection And Classification Framework

The purpose of this study is to detect and classify of sulfide type non-metallic inclusions in steel using the developed system that is based on image processing algorithms. The system also analyzes the detected and classified inclusions using extreme value distribution. The general overview of the system is shown in the Figure 1.

Extreme value distribution is a statistical distribution that predicts the expected extreme value according to data obtained. Extreme value distribution has extensive usage on many applications on different areas such as environment, finance, meteorology, civil engineering, human life [17]. Knowledge of the probability of extreme event occurrence may help the scientist or engineer to develop the system according to hard conditions. Extreme value distribution is discovered by Fisher and Tippet, then proved by Gnedenko [18]. Basically, there are three types of extreme value distributions. The probability density functions of types are as follows:

Type I $$f(x)=\frac{1}{\delta}\exp\left(-\frac{x-\lambda}{\delta}-\exp\left(-\frac{x-\lambda}{\delta}\right)\right) \quad (1)$$

Type II $$f(x)=\frac{\alpha}{\delta}\left(\frac{\delta}{x}\right)^{\alpha+1}\exp\left(-\left(\frac{\delta}{x}\right)^{\alpha}\right) \quad (2)$$

Type III $$f(x)=\frac{\alpha}{\delta}\left(\frac{x-\lambda}{\delta}\right)^{\alpha+1}\exp\left(-\left(\frac{x-\lambda}{\delta}\right)^{\alpha}\right) \quad (3)$$

The parameters λ represents location parameter; δ represents scale parameter and α represents shape parameter. Type I is also known as Gumbel extreme value distribution, Type II is also known as Frechet extreme value distribution and Type III is also known as Weibull extreme value distribution. We have used Gumbel extreme value distribution and followed the procedures in standard practice ASTM E2283 [19]. This practice applies the extreme value distribution on steel measurement to predict extreme length value. The practice is applied on oxide type inclusions and instance calculation. According to the practice, 6 specimen and their 4 sides are required for analysis. The 24 measurements are used to predict expected extreme length value. The algorithm of practice is shown in Figure 2.

In practice, Gumbel type extreme value distribution has 2 parameters; the location and scale parameters. ASTM E2283 offers maximum likelihood method to estimate these parameters, thus it gives more precise results than other methods. However, for the first estimation of these parameters, the practice offers methods of the moments due to the simplicity of calculation. The representation of parameters with method of moments as follows:

$$\lambda_{mom}=\bar{L}-0{,}5772.\delta_{mom} \quad (4)$$

$$\delta_{mom}=\frac{S_{dev}\sqrt{6}}{\pi} \quad (5)$$

Maximum likelihood method is based on the calculating of best value of parameters. The easiest way for process of maximizing parameters is maximizing of logarithm of distribution function. It formulates as follows:

$$LL=\sum_{i=1}^{n}\ln(f(x_i,\lambda,\delta)) \quad (6)$$

The maximization process is best performed with iteration of function with numerical analysis methods.

Preparing specimen is very important task for metallographic analysis. Well prepared specimens reduce the time and give results much faster; they also avoid the confusions between inclusion and inclusion like artifacts and results will be more reliable. In this study, the specimens are prepared according to ASTM E3 standard.

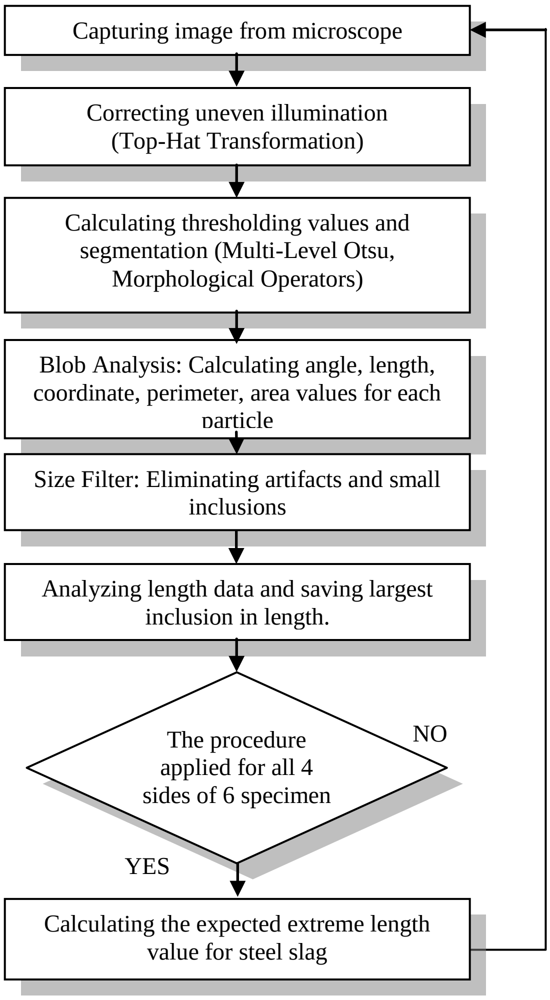


Figure 1. Overview of the framework

One of the difficulties of working with steel sample is reflection of microscope illumination lights from polished surface of sample. It causes non uniform illumination problem on the captured image and it affects the performance of segmentation results. Top-Hat transformation was applied on captured image to correct the uneven illumination. It is based on morphological opening and closing operations. If transformations are applied on light objects with dark background, it is called Top-Hat or White Top-Hat Transformation. If transformation is applied on dark objects with light background, it is called Bottom-Hat or Black Top-Hat Transformation [20].

One of the distinguishing properties of sulfide type inclusions from other types is gray level value. Sulfide types inclusions seem to be lighter than other types of inclusions. It shows that there are three threshold values with two types of inclusion and background. To calculate threshold values for segmentation, we have used Multi-Level Otsu Method [21]. This algorithm was first mentioned in 1979 by Nobuyuki Otsu and it maximizes the variance of pixel intensity between clusters. We have used threshold values for segmentation and created new images to separate inclusions according to their gray level. We have applied blob detection and analysis algorithms on every segmented image. At the end of these operations, we have calculated length, angle, perimeter, area and coordinate properties of every segmented object on the images. To eliminate the artifacts and small inclusions, we have applied size filter on segmented objects. From the filtered data we have calculated the other detection conditions mentioned in standard ASTM E45 including neighborhood, aspect ratio, number of inclusions, distance between inclusions and clusters.

III. Experimental Results

AISI 1040 Carbon Steel has been used as experimental steel. The chemical composition of the AISI 1040 steel is shown in Table 1[22].

TABLE I. CHEMICAL COMPOSITION OF THE AISI 1040 STEEL

Element[a]	C	Si	Mn	P	S
AISI 1040	*0.41*	*0.17*	*0.67*	*0.012*	*0.005*

a. *Element in wt. %, Fe=bal.*

Six pieces of specimens were cut from steel slag and were prepared according to ASTM E3. The specimens were examined by light microscopy with the magnification of 100x, and analyzed with the criteria of ASTM E45. The test area, also control area was chosen with the dimension of 160 mm^2 (16mmx10mm). The test area was scanned and analyzed with the area of 0.50 mm^2. Method D of ASTM E45 was chosen to scan and measure the specimen to obtain more reliable data from the specimen. This procedure was applied for each six specimens. Top-hat transformations were applied to solve non uniform illumination problem. Multilevel Otsu algorithm was applied to find threshold levels. Morphological and blob analysis operations were performed to obtain length and distribution data of non-metallic inclusions. The detected and classified inclusions are shown in Figure 3. Morphological characteristics of detected inclusions were showed that these inclusions are sulphide type inclusions. The maximum lengths of inclusions (exceeding acceptable length limits of ASTM E45) for each specimen are shown in Table II. The thickness limits of ASTM E45 are shown in Table III. The statistical parameters for calculation of extreme value distribution have been calculated according to ASTM E2283 standard and results of calculated parameters are shown in Table IV.

The non-metallic inclusions in AISI 1040 steel were successfully analyzed by the system developed. The number of required control area for observation to find maximum inclusion length calculated as 1000 with the equation:

$$T = \frac{1}{1-P} \tag{7}$$

The maximum expected inclusion length were calculated as 36.0622 µm using equation :

$$L = -\delta_{ML} \ln(-\ln(\frac{T-1}{T})) + \lambda_{ML} \tag{8}$$

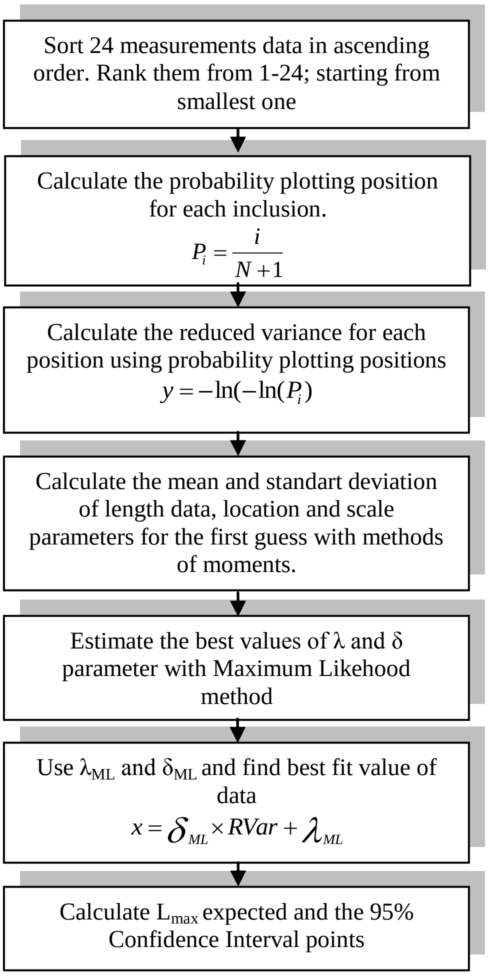


Figure 2. Extreme value distribution calculation algorithm

Consequently, the inclusion length of 36.0622 µm was found in 160 000 mm^2 total reference area. This length information can be quite useful for calculation of fatigue strength.

IV. Conclusions

In this study, we have developed a framework that automatically detects and classifies sulphide type inclusions in steel using image processing algorithms. By employing statistical Gumbel extreme value distribution, the framework also predicts the expected extreme value according to the data obtained by the framework. The knowledge of probability of expected extreme value information plays important role on extreme event occurrences. This may help scientists and engineers to design and develop systems according to hard conditions.

V. Acknowledgements

This work is supported by San-Tez Program with the grant number 0689.STZ.2014.

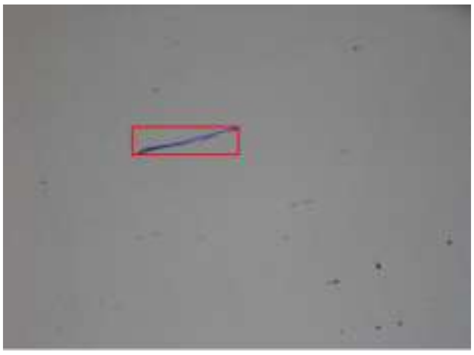
TABLE II. MAXIMUM LENGTH OF INCLUSIONS FOR ALL SPECIMEN AND SIDES

Specimen (µm)	A	B	C	D
1	*17,63*	*23*	*13,31*	*15,44*
2	*18,19*	*16.13*	*12,43*	*19,88*
3	*15,75*	*19,4*	*19,25*	*15,81*
4	*17,88*	*13,45*	*15,36*	*17,56*
5	*19,18*	*14,94*	*33*	*12,51*
6	*24,56*	*18,13*	*14,23*	*16,58*
Mean Length=17,65			***Standard Deviation=4,45***	

TABLE III. CHARACTERIZATION OF INCLUSIONS THICKNESS LIMITS IN ASTM E45

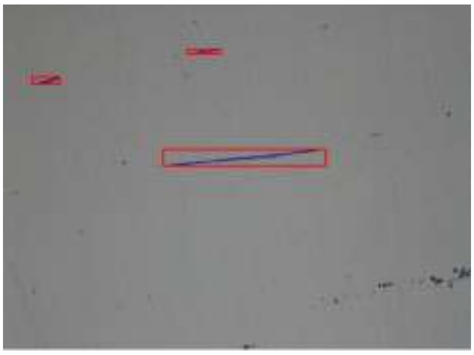
Type	Thin Series		Thick Series	
	Lower	***Upper***	***Lower***	***Upper***
A	*2*	*4*	*>4*	*12*
B	*2*	*9*	*>9*	*15*
C	*2*	*5*	*>5*	*12*
D	*2*	*8*	*>8*	*13*

1.a

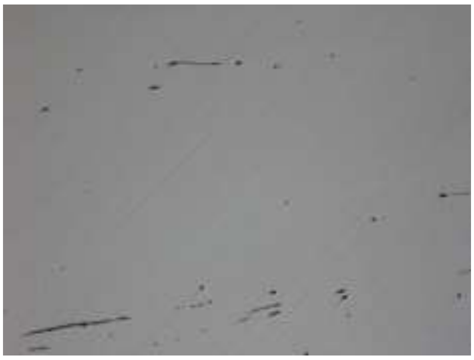


1.b.

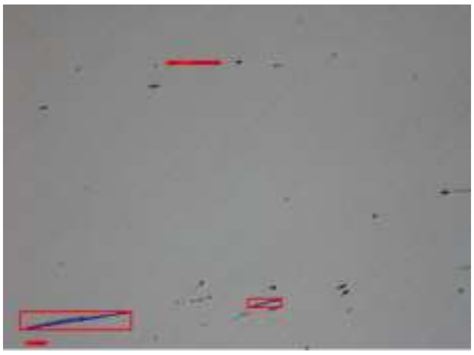
2.a.



2.b.



3.a.



3.b.

Figure 3: 1.a., 2.a., 3.a. : Images are used for analysis
1.b., 2.b., 3.b. : Resulting images, detected inclusions are shown with rectangles.

TABLE IV. STATISTICAL PARAMETERS FOR THE MEASURED INCLUSIONS

Length (Y) Data	Rank	Probability	Red.Var. (X) RV	Ln ($f(x_i, \delta, \lambda)$)	X	X_low	X_high
12,43	1	0,04	-3,12	-2,84	12,43	10,65	14,21
12,51	2	0,08	-3,063	-2,81	13,14	11,36	14,92
13,31	3	0,12	-2,59	-2,53	13,65	11,87	15,43
13,45	4	0,16	-2,52	-2,49	14,08	12,30	15,86
14,23	5	0,20	-2,26	-2,34	14,46	12,68	16,24
14,94	6	0,24	-2,13	-2,27	14,81	13,04	16,59
15,36	7	0,28	-2,09	-2,25	15,14	13,36	16,92
15,44	8	0,32	-2,08	-2,25	15,47	13,69	17,25
15,75	9	0,36	-2,074	-2,24	15,79	14,01	17,57
15,81	10	0,40	-2,074	-2,24	16,11	14,33	17,88
16,13	11	0,44	-2,08	-2,25	16,43	14,65	18,21
16,58	12	0,48	-2,10	-2,28	16,75	14,97	18,53
17,56	13	0,52	-2,21	-2,37	17,09	15,31	18,87
17,63	14	0,56	-2,23	-2,38	17,44	15,66	19,22
17,88	15	0,60	-2,27	-2,41	17,81	16,03	19,59
18,13	16	0,64	-2,31	-2,45	18,21	16,43	19,99
18,19	17	0,68	-2,32	-2,46	18,64	16,86	20,42
19,18	18	0,72	-2,53	-2,62	19,10	17,32	20,88
19,25	19	0,76	-2,55	-2,64	19,63	17,85	21,41
19,4	20	0,80	-2,58	-2,66	20,23	18,45	22,01
19,88	21	0,84	-2,70	-2,76	20,956	19,18	22,74
23	22	0,88	-3,60	-3,48	21,86	20,08	23,64
24,56	23	0,92	-4,10	-3,89	23,11	21,33	24,89
33	24	0,96	-6,94	-6,25	25,20	23,42	26,978

REFERENCES

[1] R.Kessling, "Clean Steel- a debatable concept," Metals Society, Vol 15 (5)1 1980, 161-172

[2] M Van Ende, "Formation and morphology of non-metallic inclusions in alluminium killed steels ," Doctorate Thesis, The Katholike Universiteit Leuven, January 2010

[3] Y.Murakami, "Metal fatigue: effects of small defects and nonmetallic inclusions," Elseiver, 2002

[4] C.W. Anderson, G.Shi, H.V.Atkinson, C.M. Sellars, "The precision of methods using the statistics of extremes for the estimation of the maximum size of inclusions in clean steels", Acta Materialla, Volume 48, Issue 17, Pages 4235-4246, 8 November 2000

[5] "Jernkontoret's Inclusion Chart II for the assesment of non metallic inclusions,"Swedish Standarts Instutite,SS 11 11 16.

[6] "ASTM E45: Standart test methods for determining the inclusion content of steel", American Society for Testing Materials.

[7] A. Bytyqi, N. Pukšič, M.Jenko, M.Godec, "Characterization of the inclusions in spring steel using light microscopy and scanning electron micrscopy" , Materials and Technology , Volume 45, Issue 1, pp 55-59, January 2011

[8] Y.Ren, Y.Wang, S.Li, L. Zhang, X.Zuo, S.N. Lekakh, K.Peaslee "Detection of non-metallic inclusions in steel continuous casting bllets " ,Metallurgical and Materials Transactions B, Volume 45, Issue 4, pp 1291-1303, August 2014

[9] L.M. Cabalín et all., "Large area mapping of non-metallic inclusions in stainless steel by an automated system based on laser ablation", Spectrochimica Acta, Elseiver, January 2004

[10] C.Buck, F.Bürger,J.Herwig and M.Thurau, "Rapid inclusion and defect detection system for large steel volumes", ISIJ International Volume 53, Issue 11, pp 1927-1935, July 2013

[11] A.B. Schmiedt, "Statistical modelling of non-metallic inclusions in steels and extreme value analysis," Doctorate Thesis, RWTH Aachen University, November 2012

[12] Y.Murakami, "Inclusion rating by statistics of extreme values and its application to fatigue strength prediction and quality control of materials", Journal of Research of the National Institute of Standards and Technology, Volume 99, Issue 4, July-August 1994

[13] C.W.Anderson, G.Shi, H.V. Atkinson and C.M. Sellars, "The precision of methods using the statistics of extremes for the estimation of the maximum size of incluions in clean steels", Acta Materialia,Elseiver, Volume 48, pp4235-4246, 2000

[14] S.Baretta, Y.Murakami, "Largest-extreme-value distribution analysis of multiple inclusion types in determining steel cleanliness" Metallurgical and Materials Transactions B, Volume 32, Issue 3, pp 517-523, June 2001

[15] C.W. Anderson, J. de Mare, H.Rootzen, "Methods for estimating the sizes of large inclusions in clean steels", Acta Materialia,Elseiver, Volume 53, pp 2295-2304, 2005

[16] C.W. Anderson, S.G.Coles, "The largest inclusions in a piece of steel", Extremes , Volume 5, Issue 3, Pages 237-252, September 2002

[17] S. Kotz, S. Nadarajah, "Exreme value distributions theory and applications", Imperial College Press , 2000

[18] H. Hirose, "Maximum likelihood estimation in the 3-parameter Weibull distribution. Alook through the genralized extreme-value distribution", , IEEE Transaction on Dielectrics and electrical Insulation, Volume 3, Issue 1, pp 43-55, Febuary 1996

[19] "ASTM E2283: Standard practice for extreme value analysis of nonmetallic inclusions in steel and other microstructural features", American Society for Testing Materials.

[20] R.C. Gonzales, R.E.Woods, "Digital image processing" Pearson Education, Third Edition, 2008

[21] N.Otsu, "A threshold selection method from gray-level histograms". IEEE Trans. Sys., Man., Cyber. 9 pp 62-66, January 1979.

[22] C.Meric, S.Sahin, S.S. Yilmaz, "Investigation of the effect on boride layer of powder particle size used in boronizing with solid boron-yielding substances" Materials Research Bulletin, Volume35, Issue 13,pp:2165-2172, October 2000.

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