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Characterization of Impact Fracture Surfaces under Different Processing Conditions of 7075 Al Alloy using Image Texture Analysis

Prosenjit Das[1], Samik Dutta[2], H. Roy[2], R. Jayaganthan[3]
[1]Foundry Group, Central Mechanical Engineering Research Institute, Durgapur, India
Email: prosenjit.sct.cmeri@gmail.com
[2]Central Mechanical Engineering Research Institute, Durgapur, India
Email:{samikhere,himadri9504}@gmail.com
[3]Department of Metallurgical & Materials Engineering, IIT Roorkee, Roorkee, India.
Email: metarj@gmail.com

***Abstract* - A fracture surface keeps an imprint of the entire deformation process that the material has been subjected. Therefore, micro feature extraction using image analysis can reveal significant information regarding the failure of any component. Texture analysis incorporating gray-level co-occurrence matrix and run length statistics have been used on factographs generated by impact tests under different processing conditions of an 7075 Al alloy. The different processing conditions include solution treated bulk alloy, cryo-rolled at 40 % and 70 % of the thickness and finally cryo-rolled + peak aged form. The results obtained from the investigation reveal systematic correlation of image statistical texture properties with impact toughness generated at different processing conditions. The concept of applicability of machine vision techniques to material characterization is highlighted.**

***Index Terms* - Impact energy, Factograph, Texture analysis, GLCM, Run Length Statistics**

I. INTRODUCTION

The development of high strength Al alloys for aerospace and automobile applications is ever growing due to the importance of extending service life of the structural components fabricated from these alloys [1]. Mechanical properties of the Al alloys can be further improved by Severe plastic deformation (SPD) techniques, which are now widely used for the production of ultrafine-grained (UFG) microstructures in bulk metals. Rolling of pure metals and alloys in cryogenic temperature suppresses dynamic recovery and the density of accumulated dislocations, these higher density of dislocations rearrange themselves into sub-structures followed by the formation of ultrafine grain structures (ufg) with high angle grain boundaries with the multiple cryo-rolling (CR) passes [2,3]. However with the recent development of machine vision systems, several researchers used the statistical image texture analysis techniques for surface roughness evaluation of metal surfaces. Gadelmawla used GLCM technique for calculating the rugosity of the surface [4]. In some researches the co-occurrence matrices were calculated from the machined surface images to determine the surface texture properties [5-7]. Myshkin et al. [8] used a special type of co-occurrence matrix with the concept of multi-level roughness to determine the surface roughness in microscale from the AFM images. Kassim et al. [9] investigated surface images of turned workpiece (AISI 1045 and AISI 4340 material) by runlength statistics technique. End milled surface images were also analyzed using fractal analysis for sharp, semi-dull and dull tools [10]. CCD camera with high magnification lens with proper lighting systems were used to capture the surface images in the above mentioned researches [4-7, 9-11]. Factographs, obtained from Scanning Electron Microscope (SEM), carries the information about its the surface properties. Recently, Das et al. [12,13], in a series of investigations, have attempted to correlate fracture morphologies (from SEM factographs) under different form of loading with mechanical properties and obtained a generalized trend in the variation of void characteristics with mechanical properties. However it is faster approach to apply image texture analysis method for automatic analysis of factographs. In this work an attempt has been made to correlate the impact toughness obtained at different processing conditions of Al 7075 alloy with normalized values of statistical image texture parameters (from GLCM and RLS techniques).

II. EXPERIMENTAL PROCEDURE

The Al 7075 alloy with the chemical composition of 6.04 Zn, 3.64 Mg, 1.76Cu, 0.50 Cr, 0.2 Si, 0.15 Mn, 0.57 Fe, and Al balance in the form of extruded ingot with the diameter of 50 mm, used in the present work, has been procured from Hindustan Aeronautics Ltd., Bangalore, India. The as received Al extruded ingot was machined into small plates and then solution treated (ST) at 490^{0}C for 6 hours followed by quenching treatment in water at room temperature. The solution treated Al 7075 alloy plates were subjected to rolling at cryogenic temperature to achieve 40% and 70% thickness reduction. The samples were soaked in liquid nitrogen taken in the cryocan for 30 minutes prior to each roll pass during the rolling process. The diameter of the rolls was 110 mm and the rolling speed was 8 rpm. The temperature before and after rolling of the samples was -190^{o}C and -150^{o}C, respectively. The solid lubricant, $MoSi_2$, has been used during the rolling process to minimize the frictional heat. The thickness reduction per pass was 5% but many passes were given to achieve the required reduction of the samples. For impact testing test, CR Al alloy and original samples were cut from longitudinal (rolling) direction. The in plane specimen dimension was 10 mm X 55 mm with a 2 mm deep, 450 V-notch having a 0.25 mm tip radius at the center of the specimen, prepared as per the ASTM Standard E-23-07ae1. The microstructural characteristics of the starting bulk Al alloy and cryorolled Al 7075 alloys and also their fracture surfaces were characterized by using FE-SEM and SEM. Factographs, taken using SEM was processed by digital image processing technique. Firstly, factographs were compensated from inhomogeneous illumination and then those illumination compensated images were analyzed using statistical texture analysis techniques by Grey Level Co-occurrence Matrix (GLCM) and Run Length Statistics (RLS). These techniques are discussed briefly in the following section.

III. IMAGE PROCESSING TECHNIQUES

A digital image processing method for compensating the inhomogeneous illumination is used for each image as proposed by Kassim et al. [7]. Each original image is recovered from inhomogeneous illumination using the expression:

$$t(x,y) = \frac{g(x,y) - \hat{i}_1(x,y)}{\hat{i}_2(x,y)} . \tag{1}$$

Where, $t(x, y)$ is the recovered image from the original image $g(x,y)$

Where $\hat{i}_1(x,y) = LP\{g(x,y)\}$. and

$$\hat{i}_2(x,y) = (LP\{[g(x,y) - \hat{i}_1(x,y)]^2\})^{0.5}.$$

Where, LP is a low pass filter and here Gaussian filtering technique is used with standard deviation (σ) = 10.

The Grey Level Co-occurrence Matrix (GLCM) is produced by counting the number of occurrences of pixel pairs of given intensities at a given displacement. To produce a GLCM from an image, a small region is defined by the nearest neighbor to any given pixel. Then a two-dimensional map (Fig. 1) of their frequency of occurrence is formed as a GLCM [8]. The upper matrix is original image where the elements in the matrix indicate the grey intensity values of pixels. The value of row *i* and column *j* in the lower matrix gives the number of times that a pixel with the value *j* was to the immediate right of a pixel with the value *i*. Hence, the value 3 in the second column and third row of the lower matrix indicates that a pixel value of 10 is to the right of a pixel with the value 20 counted 3 times. The neighbor pixel is chosen to be the one to the right of each reference pixel. This can also be expressed as a (1, 0) relation: 1 pixel in the x-direction and 0 pixel in the *y* direction. After compensating

Original image matrix

5	5	10	5
20	10	5	5
5	20	10	5
5	5	20	10

GLCM of the image matrix

i \ j	5	10	20
5	3	1	2
10	3	0	0
20	0	3	0

Figure 1. Original image matrix and its GLCM.

1	1	2	2
3	4	3	2
5	1	2	1
4	4	5	5

i \ j	1	2
1	2	1
2	2	1
3	1	0
4	1	1
5	1	1

Figure 2. (a) Original Image Matrix (b) Corresponding Run-length matrix

illumination of each image, an entropy value is determined using expression (2) and a GLCM is created.

$$Entropy = -\sum_i \sum_j P(i,j) \log P(i,j). \tag{2}$$

and entropy (2), which is a representative of "randomness", is also calculated.

Where, $P(i, j)$ is the histogram count of the illumination compensated image. One statistical property namely energy is representing orderliness and it is calculated from the GLCM of each illumination compensated image using (3).

$$Energy = \sum_i \sum_j p^2(i,j). \tag{3}$$

Where, $p(i, j)$ is the frequency of occurrence of pixel *i* and *j* in a particular direction. Run-length statistics is a multi-order statistical texture analysis technique which is applied on the illumination compensated images. A typical run length matrix constructed from an image matrix is shown in Fig. 2(b). Consecutive pixels of the same grey value or level in either the horizontal or vertical direction constitute a run. In this paper, the run-length matrix is evaluated in the horizontal direction.

Two statistical parameters are taken from run length matrix namely: (i) Low Grey-level Run Emphasis (LGRE), and (ii) High Gray-level Run Emphasis (HGRE). They are calculated from illumination compensated images. The equations are given below as (4) and (5):

$$LGRE = \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{(R(i,j)/n_r)}{j^2}. \tag{4}$$

$$HGRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} R(i,j).i^2. \tag{5}$$

Where n_r = total number of runs, $R(i, j)$'s are the elements of runlength matrix.

IV. RESULTS AND DISCUSSION

Fig. 3 shows the impact toughness properties of bulk Al 7075 alloy, its cryorolled (CR) form (40% and 70% thickness reduced) and cryorolled + peak aged form. It is observed that the impact toughness of the CR samples increases due to breakage of the large aluminum dendrites, grain fragment with high angle boundaries and formation of ultrafine grains with the increasing number of cryorolling passes [12]. Impact energy of starting bulk Al alloy is 17J, and it has increased to 21J (24% increase) and 27J (nearly 60% increase) after 40% and 70% thickness reductions, respectively. The effect of optimum heat treatment (HT) conditions (short annealing + ageing) conditions is not well pronounced over the impact toughness properties of the CR Al7075 alloy as shown in Figure 3. It is clear from this figure that precipitation hardening does not improve impact strength of CR Al alloy, which may be due to high strain rate involved in impact testing and preferential fracture path facilitated by precipitates**.**

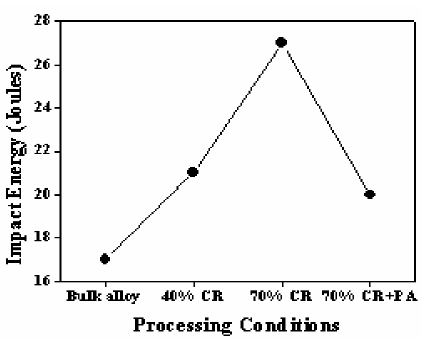


Figure 3. Impact energy plot of 7075 Al alloy.

Fig. 4 shows the SEM fractographs of samples, tested under impact loading, of the Al 7075 alloy cryorolled at different percentage of thickness reduction. Charpy impact specimen's exhibits shear induced fracture. Due to high strain rate involved in the impact specimens, the fracture surface shows complete dimple fracture and dimple size gradually decreased with increasing % reduction obtained by cryorolling. The factographs of samples were compensated from inhomogeneous illumination and then entropy of those illumination compensated factographs are shown Fig. 5. After that, the GLCM were determined from illumination compensated images in (1, 0) direction and run length matrix were determined from illumination compensated images in horizontal direction. Then energy, LGRE and HGRE parameters of those images were calculated. Attempts have been made in this investigation to explain the correlation between the variation in impact energy with image texture properties like entropy, energy, LGRE, HGRE, which are shown in Fig. 6.

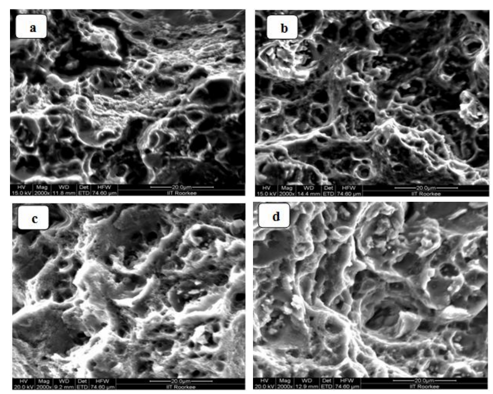


Figure 4. Fracture surface morphology of Al 7075 alloys, under impact loading, cryorolled at different percentage of reduction: (a) Starting material, (b) 40% reduction, (c) 70% reduction (d) 70% reduction after aging.

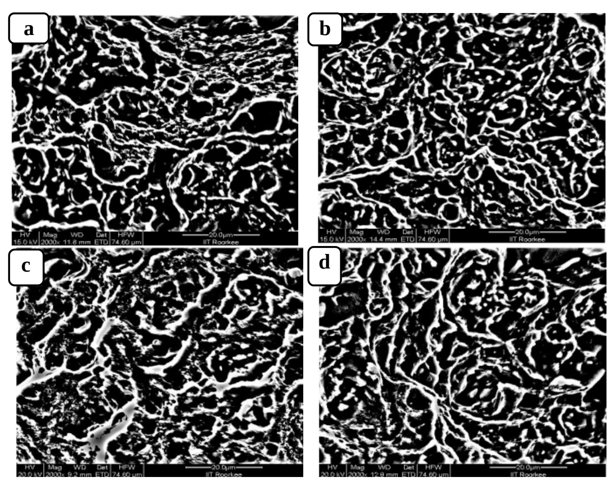
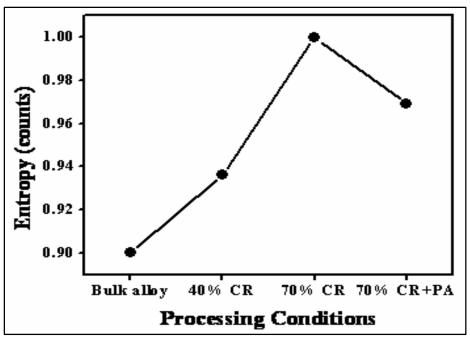


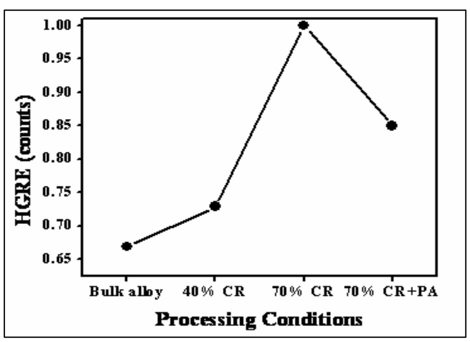
Figure 5. Illumination compensated factographs of Al 7075 alloys, under impact loading, cryorolled at different percentage of reduction: (a) Starting material, (b) 40% reduction, (c) 70% reduction (d) 70% reduction after aging.

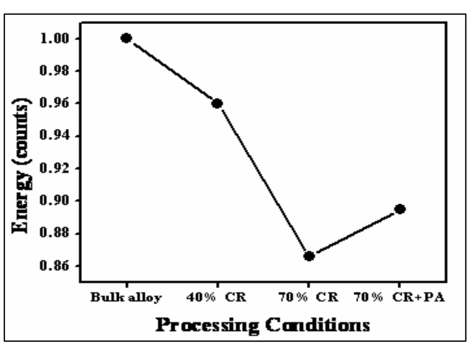
Actual impact energy, entropy, energy (from GLCM), LGRE and HGRE were plotted against processing conditions of the samples. Image properties were also normalized against their maximum values. It is seen from the plots that entropy and HGRE parameters are behaving same like impact energy and energy and LGRE parameters are showing the reverse behavior of impact energy.

V. CONCLUSIONS

Entropy of the image (representing "randomness") and HGRE are following same trend as that of impact energy. On the other hand, energy (representing "orderliness") and LGRE are following just reverse trend as that of impact energy. In this investigation second order and higher order statistical texture analysis are useful for investigating the impact properties of any samples. There exists a systematic variation in image texture properties of the fracture surface with impact toughness.







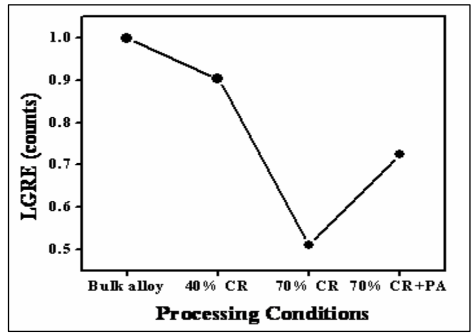


Figure 6. Plots of image texture parameters entropy, energy, HGRE and LGRE against processing conditions

However, it has been found that application of advanced automated image processing techniques, a recently developed tool in the area of textural fractography, can even provide better insight to materials properties. So a novel path for automatic detection of nature of variation of impact toughness from fractographs can be envisioned from this research.

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