IDENTIFICATION OF THE DUCTILE FRACTURE AREA OF X70 STEEL FROM DWTT BROKEN SPECIMENS

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Abstract

Fracture surfaces of X70 steel DWTT broken samples are analysed using new surface evaluation concept. The presented approach is an alternative to an expert determining a ratio between the ductile and brittle fracture area. The analysed data source, i.e. x, y and z coordinates of points of fracture surface, comes from 3D scan using Limess Measurement Technique. Beside formerly used fractal geometry approach, new concept based on normal vector characteristics is used. The fracture surface net is generated by triangulation of points of fracture surface. For every triangle, the normal vector is computed. Thereafter, normal vector characteristics are clustered via k-means++ clustering algorithm. Application of the algorithm improves the correct detection of the brittle and ductile fractures significantly, so that the achieved clusters highly correspond to the real distribution of the ductile and brittle fracture areas on DWTT surface. Furthermore, applied methods are computationally very fast, so that it is possible to apply them for the scans with considerably higher magnitude. The correctness of the final cluster results are evaluated comparing with the real displacement of the brittle and ductile fracture, and by using various theoretical approaches.

Keywords: DWTT samples, ductile and brittle fracture, k-means clustering

1. INTRODUCTION

The correct identification of the fracture surfaces is very important for an evaluation of fracture resistance. Nowadays, there are many mechanical tests for determining a fracture resistance, e. g. Charpy V-notch test or Drop Weight Tear Test (DWTT) [6]. In our paper, a fracture surfaces of the broken DWTT specimens are studied using commercially produced samples of API 5L X-70 sheet steel with thickness 18.7 mm.

After realizing DWTT, the tested surface is evaluated by an expert, who evaluates a ratio between a ductile and brittle fracture. Analysis by a specialist has many advantages, however, amount of human error is also incorporated. In some cases, expert opinions may vary significantly, see [7]. Alternative to an expert evaluation is realizing 3D scan. The fracture surfaces were scanned by 3D camera using Limess Measurement.

The aim of this paper is to present an alternative method of the fracture surface evaluation. To determine displacement of the brittle and ductile fracture various normal vector characteristics are used. The Normal vector characteristics are an alternative approach to the fractal geometry concept, which is often used in fracture surface characterization [2]. However, normal vector characteristics compare to fractal dimension evaluates fracture area in certain place see [11].

The displacement of normal vector characteristics well corresponds to the real displacement of the ductile and brittle fracture areas. Normal vector outputs can be greatly improved applying appropriate techniques. Dividing normal vector characteristics to a ductile and brittle fracture can be seen as clustering problem. In this sense, we will apply k-means++ algorithm [1]. The k-means++ algorithm seems to be the best choice of all Lloyd type algorithms for the presented problem see [10]. Final clustering results are compared with the real ductile and brittle fracture displacement. Furthermore, the various clustering criterions are taken into account [3].

2. INVESTIGATED MATERIALS AND METHODS

2.1. DWTT specimens

The fracture surfaces of the broken DWTT specimens are studied using samples from commercially produced API 5 L X-70 sheets Cr-Mn steel with thickness of 18.7 mm. The steel was austenitized at 1200°C, rolled with an initial temperature of 985°C, and final rolling temperature of 832°C. It was then water-cooled from 800°C to 465° at 9.1 °C/s. Basic mechanical properties of the steel at 20°C were determined by tensile testing on standard specimens with a circular cross-section of diameter 4 mm at deformation speed 0.008 s^{-1}. The yield strength Rp0.2 > 485 MPa and the tensile strength Rm > 570 MPa.

The proposed methods of evaluating the ductile fracture percentage (i.e. the percentage of the fracture surface displaying ductile fracture) were tested on ten DWTT specimens with dimensions 300 x 76 mm and with the same thickness as the sheet steel (18.7 mm). The specimens were press-notched to a depth of 5.1 mm. All DWTT specimens were tested at -20°C. The DWTT specimens were broken by a falling weight of 800 kg on Drop Weight Tester 40 apparatus. Fracture surface of broken DWTT specimen of investigated API 5L X-70 steel at -20°C is given in **Figure 1**.

The DWTT specimen fracture surfaces were photographed using 3D camera produced by Limess Measurement Technique and Software. 3D camera projects straight lines into DWTT specimen and photographs deformed image of the lines. After using the projection, the real surface is represented by discrete points recorded in their x, y and z coordinates. The scan was not realized with high magnification, so that the specimen is represented with approximately 50 000 points. Computer surface visualization is presented in the **Figure 2**.

Figure 1 DWTT surface specimen

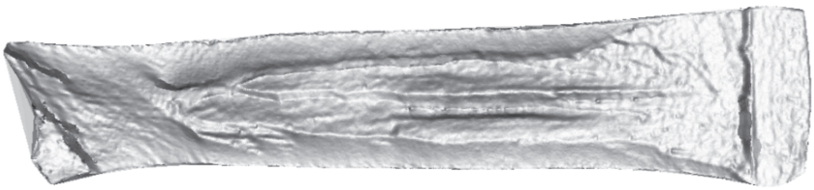

Figure 2 DWTT surface visualization

2.2. Normal vector characteristics

To determine normal vectors, the fracture surface is covered with the net of triangles. The vertices of triangle correspond to real measurements of the fracture surface. To create the triangle net, the Delaunay triangulation was used, see [4]. The Delaunay triangulation maximizes the lower angle of each triangle, so that the final triangulation contents as regular as possible triangles. For every triangle, the unit vector perpendicular to the triangle (normal vector) is calculated. Total amount of normal vector is over 100 000 values (greater than former data source). Every normal vector is placed to the centre of gravity of the appropriate triangle for purposes of data visualization.

For an every (unit) vector, we will use the length of its y, z component. The components describe how much is the surface tilted in the x, y, z directions. Furthermore we will consider changes of x, y and z components of two neighbouring vectors with the greatest angle deviation. For given normal vector $n_i = (x_i, y_i, z_i)$ related to the centre of gravity $T_i = (x_i^T, y_i^T, z_i^T)$ of the triangle Δ_i, we take into account x_i, y_i, z_i. For every fixed i, we chose a neighbour Δ_j of the triangle Δ_i with a maximal angular deviation of related normal vectors; so that we compute absolute differences of the change of vector component

$$d_i^x = \frac{|x_j - x_i|}{x_i^T - x_j^T} \; d_i^y = \frac{|y_j - y_i|}{y_i^T - y_j^T} \; d_i^z = \frac{|z_j - z_i|}{z_i^T - z_j^T}. \tag{1}$$

Let us summarize, that every triangle with the centre of gravity T_i is evaluated with three values normal vector components x_i, y_i, z_i and absolute difference d_i^x, d_i^y, d_i^z.

2.3. K-means clustering

The k-means is a well-known clustering algorithm. It divides the data set $X \subset \mathbb{R}^d$ to k clusters $C_1, \dots, C_k$, so every $x \in X$ belongs to the cluster C_i with the nearest center c_i. The k-means solves the problem of minimizing the potential function ϕ

$$\phi = \sum_{x \in X} \sum_{c_i \in C} \|x - c_i\|^2 \tag{2}$$

with respect to C.

Principally the problem of minimizing the potential function can hardly be solved by finding the best solution from all possible realizations. K-means solve the (2) in finding suboptimal solution with respect to the choice of initial centres (or clusters). The basic procedure of the algorithm can be described in the following way:

- Choose k initial centres $\{c_1, c_2, \dots, c_k\}$.
- Assign each observation x to the cluster $(1, \dots, k)$ with the "nearest" center.
- Set new centre as a mean (for Euclidean metric) of every cluster.
- Repeat previous two steps until no cluster C_i changes.

The results of the k-means depend on an initial choice of centres. We use the k-means++ variant, where the initial centres are achieved using weighted probability, see [1]. Since the algorithm achieves a local minimum of potential function, we use 10x repeat of the algorithm choosing the solution with the smallest value of potential function.

One of the disadvantages of the K-means is the fact, that it does not optimize an amount of the clusters. There are many criteria and approaches to find the best amount of the clusters for the given problem. In the presented paper we use Calinski-Harabasz (CHI) [3] and Davies-Bouldin (DBI) [5] indexes. Both criterions compare within-cluster and between-cluster distances. We choose a number of clusters with the highest CHI and with the lowest DBI criterion.

3. RESULTS AND DISCUSSIONS

In this section, we discuss the achieved results of our approach for the detections of the brittle and ductile fracture types, which is presented in the sections above.

In **Table 1**, the evaluation indices of the Calinski-Harabasz and Davies-Bouldin criterions are presented.The best result in k-means clustering for normal vector components can be achieved in case of two clusters - according to CHI and four clusters according to DBI. In **Figure 2**, the result of k-means clustering with two clusters is visualized. In this case, the orange cluster represents the ductile fracture area and the light grey represents the brittle fracture area. The four clusters results are presented in the **Figure 4**. In this case the orange cluster corresponds to the ductile fracture area. The brittle fracture is represented with two colours light grey (central part) and red (right part of the specimen). The notch is represented with light red colour. Some inaccuracies are seen at the borders of the fracture surface and at the high plastic deformation area (down on the left side).

According CHI and DBI criterions, the best result for (absolute) normal vector differences can be achieved using two clusters. The result is presented in the **Figure 5**. The orange cluster corresponds to the ductile fracture area. The light grey corresponds to the brittle fracture area. Compare to results of normal vector components the differences clustering are loaded with more inaccuracies. The greatest error in the ductile identification is in the central part of the specimen. Other inaccuracies can be seen on the left part of the specimen in the area of high plastic deformation (according to the [8]). In the other hand, application of differences is much more useful in the fracture edge detection. (the edges almost behaves as a border between ductile and brittle fracture).

Table 1 Evaluation of k-means++ results by Calinski-Harabasz and Davies-Bouldin

	Normal vector components		Normal vector differences	
Number of clusters	CHI	DBI	CHI	DBI
2	**1.2263e+05**	0.8612	**1.4096e+03**	**7.3484**
3	1.0801e+05	0.9642	686.6759	12.2589
4	1.0809e+05	**0.8518**	671.5789	10.7777
5	1.0406e+05	0.9652	679.5739	13.1723
6	9.8080e+04	0.8805	672.8802	12.8600
7	9.5414e+04	0.9089	560.1891	13.7480
8	9.4063e+04	0.9213	478.6658	15.0935
9	9.2936e+04	0.9215	441.1130	14.8978

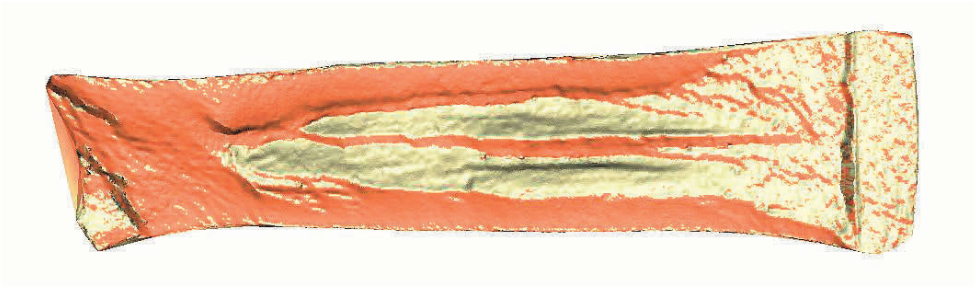

Figure 3 Clustering of normal vector components characteristics (2 clusters)

Figure 4 Clustering of normal vector components characteristics (4 clusters)

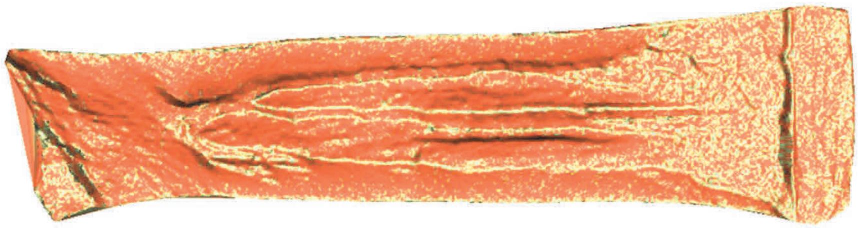

Figure 5 Clustering of normal vector differences characteristics (2 clusters)

4. CONCLUSSIONS

A detailed quantitative fractographic analysis of fracture surfaces of X70 steel DWTT specimens was presented in order to investigate new possible ways of evaluating its character, especially the ductile fracture percentage, independent to individual observation. The fracture area was evaluated with three normal vector components and three absolute differences. Thereafter the characteristics were processed with k-means++ algorithm. The achieved results highly correspond to the real displacement of the brittle and ductile fracture area. However, some inaccuracies also occur. Both normal vector components and differences are useful tool for fracture surface characterization. The vector components results are more accurate in some areas of the ductile fracture area in general. The absolute differences are further more effective in edge identification.

Very promising result was achieved applying a simple k-means++ clustering algorithm. The advantage of the k-means++ is the high computational effectiveness. The algorithm can be applied on considerably bigger data source (approximately few millions of values for common PC). The specification of the algorithm is that it comes from the family of unsupervised learning algorithms. It is no need to choose the area with pure brittle and ductile fracture area e. g. training sets in case of supervised Machine learning methods before the start of the algorithm. In further research, we aim to compare the k-means++ with supervised machine learning methods, e. g. support vector machines or neural network approaches.

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