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A Machine Learning Program for Impact Fracture Analysis

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머신러닝을 이용한 충격파면 해석에 관한 연구

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ABSTRACT

Analysis of the fracture surface is one of the most important methods for determining the cause of equipment structural failure. Whether structural failure is caused by impact or fatigue is necessary information in industrial fields. For ferrous and non-ferrous metal materials, two fracture phenomena are generated on the fracture surface: ductile and brittle fractures.

In this study, machine learning predicts whether the fracture is based on ductile or brittle when structurural failure is caused by impact. The K-means algorithm calculates this ratio by clustering the brittle and ductile fracture data from a photograph of the impact fracture surface, unlike the existing method, which calculates the fracture surface ratio by comparison with the grid type or the reference fracture surface shape.

Keywords : Machine Learning(기계학습), K-means Algorithm(K-Means 알고리즘), Clustering(군집화), Charpy Impact test(충격시험), Fracture Surface Shape(파면형상)

1. Introduction

Accident Fracture surface analysis is essential[1-3] to determine whether equipment structural failure is caused by impact or fatigue. However, it is difficult to distinguish between impact and fatigue fractures because they appear similar[1]. For ferrous and non-ferrous metals[4-7], the impact fracture surface is characterized by a combination of ductile and brittle fractures. The fatigue fracture surface is characterized by dimple and cleavage fractures along with brittle and ductile fractures. The combination of fracture types present depends on the environment and the properties of the material[1, 4-7]. In particular, the fracture characteristics vary according to temperature: brittle fracture dominates at low temperatures, and ductile fracture dominates at high temperatures[1-5]. Impact tests determine impact fracture characteristics according operating temperature of the equipment[4-8].

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Machine learning is a subfield of artificial intelligence wherein algorithms make predictions or decisions based on training data in the absence of explicit instructions[10]. The K-means algorithm is an unsupervised machine learning approach that can perform meaningful classification of images via cluster analysis.[4, 10-12]

The existing methods of measuring the ratio of brittle fracture surface and ductile fracture surface include a method using grid and a method through comparison with existing standard fracture rate table. By contrast, the K-means algorithm is a simple method to calculate the brittle fracture surface ratio by clustering the brittle fracture surface and the ductile fracture surface from a photograph of the impact fracture surface shape. The reliability of the K-means algorithm for predicting impact fractures was evaluated by comparing with standard shear fracture rate chart.

2. K-means Algorithm

The idea of K-means was started by Hugo Steinhaus in 1956 (Steinhaus, Hugo(1957)), ans then term “K-means” was first used by James MacQueen (MacQueen, J. B. (1967)).

The K-means algorithm is one of unsupervised machine learning methods and It automatically clusters data in a number selected by user. It is simple and easy way to classify data using their feature data vectors. Also, it can classify areas from image with parameters representing the features.

K-means algorithm works as shown in Figure 1. In the first step, a random representative vector is generated as shown in Figure 1(a), and the distance from each data point to the representative vector is calculated. The data points closest to the representative vector form a cluster, as shown in Figure 1(b). After that, as shown in Figure 1(c), the centroid of the clustered data is set as the new representative vector, and clustering is performed again as shown in Figure 1(d). Clustering and updating the representative vector repeat as shown in Figures 1(e), 1(f), 1(g), 1(h). Clustering is complete if there is no change in the result or the iteration limit is reached[4, 10].

The K-means algorithm extracts information from an image via clustering[4, 10, 13]. The K-means algorithm simply classify the class by setting the number of cluster and the data vectors which can recognize class of data.

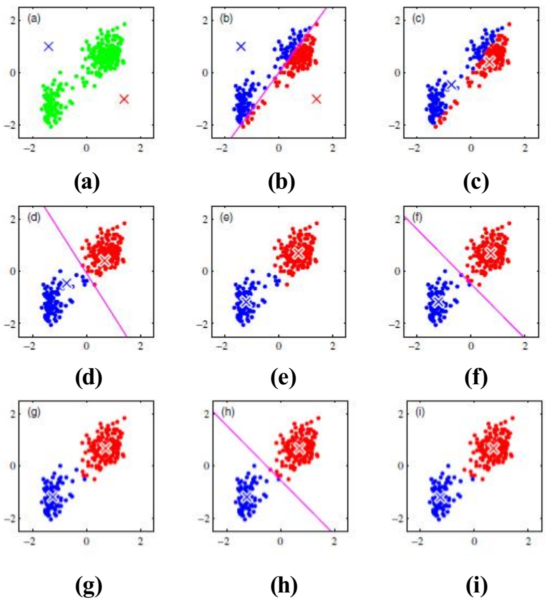


Fig. 1 Illustration of the K-means algorithm using the re-scaled Old Faithful data set[10]

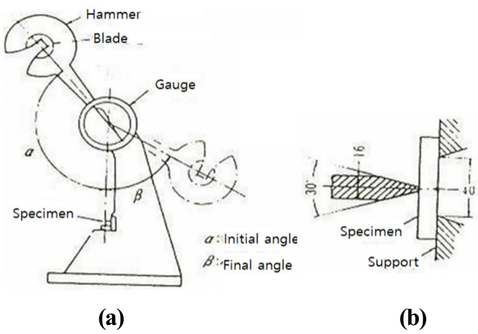


Fig. 2 The schematic of Charpy impact testing machine[5-6]

3. Impact Test Method

3.1 Charpy Impact Test

The Charpy impact test determines the impact resistance of a test piece when an instantaneous load is applied to the material. The Charpy impact test is performed by supporting both ends of the specimen on the anvil, shown in Figure 2(b), of the Charpy impact tester, shown in Figure 2(a). The hammer swings down, and the impact tester measures the energy required to fracture the specimen[4-6, 8, 14]. Charpy test was conducted under room temperature and its specimen was used for fracture surface classification.

3.2 Charpy Impact Fracture Surface Analysis Method

As Shown in Figure 3, proportion of fracture types depends on temperature, and the point at which the main fracture type changes is called ductile-brittle transition temperature (DBTT). DBTT is obtained by calculating using upper transition temperature and lower transition temperature which temperature is when the brittle fracture surface ratio is 0% or 100%. In the case of brittle fracture, the fracture energy of the specimen rapidly decreases during the impact test, and fracture by impact occurs easily at low temperatures. Because impact failure easily occurs at lower temperatures, it is important to study metal impact characteristics in a cryogenic environment[5-8]. To obtain DBTT, it is required to improve fracture classification method.

The fracture surface of the impact test piece is shown in Figure 4, and can be divided into brittle fracture surface, ductile fracture surface, and notch. Figure 4 shows the fracture surface of the impact test piece, with the brittle fracture surface at the center, and the ductile fracture surface at the edge.

The brittle fracture ratio is the proportion of brittle fracture when a material is fractured. This is

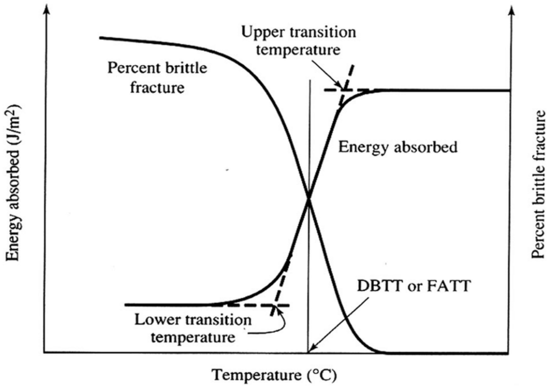


Fig. 3 Temperature-percent brittle fracture graph[15]

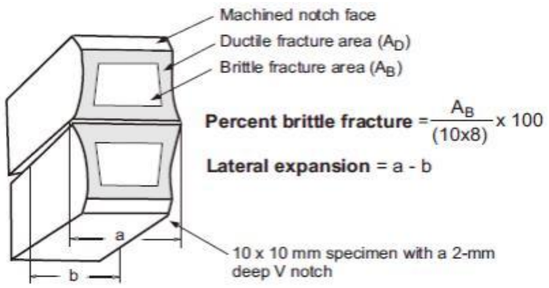
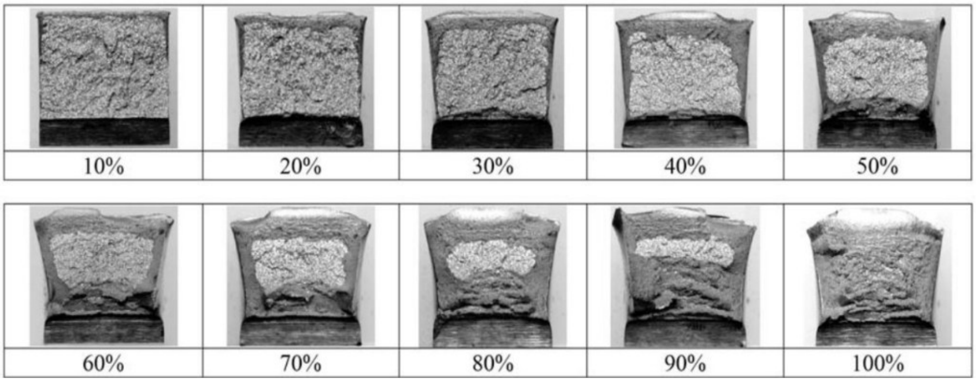


Fig. 4 Shape of fracture appearance of Charpy impact specimen[16]

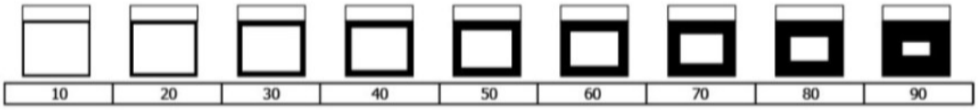
calculated by dividing the brittle fracture surface area by the total fracture surface area. Currently, brittle fracture surface area is measured via using grid type or simply comparing fracture surface with a standard fracture ratio table, but these methods can be time consuming and inaccurate because it is subjective to comparing shape of fracture surface[2, 4-6].

4. Fracture Surface Analysis Program Design

The fracture surface analysis program is written in MATLAB and uses the K-means function provided by MATLAB. The structure of the K-means function is[13]



(a) Shear Fracture Appearance Charts



(b) Guide for Estimating Shear Fracture Appearance

Fig. 5 Standard shear fracture appearance charts[5]

[idx,C]
= kmeans(X,K,'distance','sq Euclidean','Replicates',10);

Here, X denotes input data, K denotes the number of clusters, ‘distance’ denotes the use of the classification method using the distance between data, ‘sq Euclidean’ indicates that the distance is calculated using a commonly calculated Euclidean distance, an ‘Replicates’ is a function to set the number of repetitions to avoid the local minimum.[13] The output data ‘idx’ returns indexes which indicate data classified classes. So, it is possible to find which area the image pixels belong to. And output data ‘C’ returns representative vectors of classes.

Figure 5(a) shows the standard fracture surface ratio table. Also, Figure 5(a) was used for performance measurement. Figure 5(b) shows a guide for estimating impact fracture appearance[5].

The image shown in Figure 6 is pre-processed to remove the notch, adjust image size to a constant, and convert the image from RGB color space to La*b* color space converting 3 channels color to 1 channel color by using only Luminance from La*b*. By leaving only the image to be classified, as shown in Figure 6, the program then divides the image into three areas: brittle fracture surface, ductile fracture surface, and background by set K as 3.

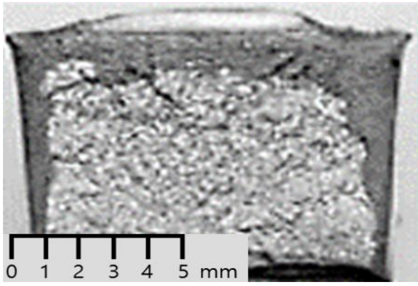
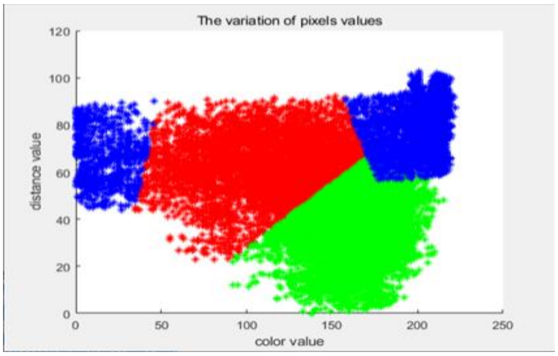
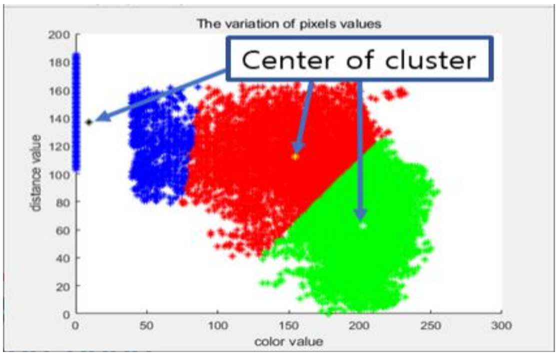


Fig. 6 Pre-Processed Fracture Appearance Image

To classify the fracture surface using the K-means algorithm, a parameter for the pixel location is added because the parameter for color alone is insufficient to describe the feature, and this value increases as the distance from the center increases.

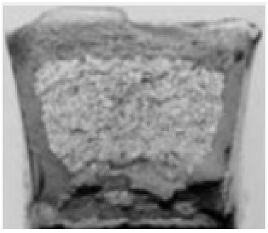


(a) Background region not removed

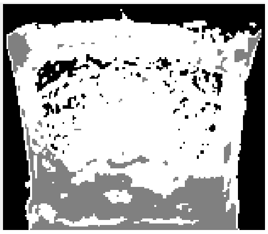


(b) Background region removed

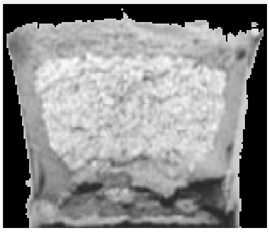
Fig. 7 The distribution of pixel data values



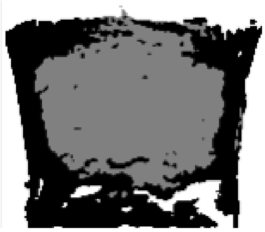
(a)



(b)



(c)



(d)

Fig. 8 The results of clustering of fracture appearance based on K-means algorithm

Now, the program separates image background from the fracture surface. By setting the number of clusters to three, the clusters at the edges are recognized as the background, and all the background color values are changed to 0. The fracture surface area and the background area are now separate and the pixels in the fracture surface area are counted. Figure 7 shows color and location values for each pixel and shows clusters classified by color. Figure 7(a) shows when the background pixel is not classified separately, and Figure 7(b) shows the distribution when the color value of the background pixels is set to 0.

The next step of the program applies the K-means algorithm again to further classify the fracture surface into brittle fracture surface and ductile fracture surface. The reason the program proceeded in two steps is to correct the misclassified area of the fracture surface as a background.

After the fracture surface is completely classified, the program starts to count pixels of each area and calculate brittle fracture surface ratio by dividing brittle pixels and all of fracture surface pixels. Then, the results are printed in the program.

Figure 8 shows all the steps of the machine learning program. Figure 8(a) shows the image of a fracture surface that has been sized and transformed to La*b* color space. The K-means algorithm then categorizes that image into three clusters, as shown in Figure 8(b). When the outer area of the image is classified as background and given a color value of 0, the image in Figure 8(c) is the result. Applying the K-means algorithm again yields the image shown in Figure 8(d).

5. Results and Discussion

5.1 Machine Learning Classification of a Fracture Surface

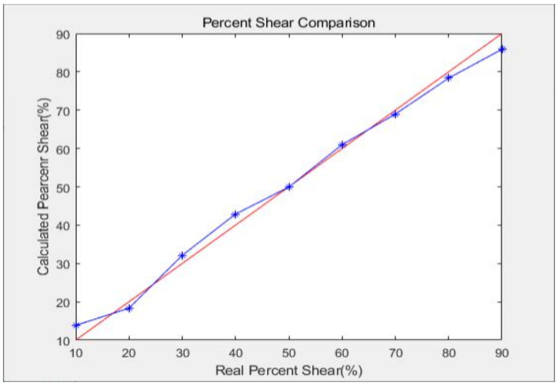


Fig. 9 The comparison between real percent shear and calculated percent shear by K-means algorithm

The program was executed using each image from standard fracture surface ratio table in the Figure 5(a) to obtain the results shown in Figure 9, which is a graph of the brittle fracture surface ratio given by the standard fracture surface table and the brittle fracture surface ratio calculated via machine learning. The raw data of Figure 9 is shown in Table 1.

As shown in Figure 9 and Table 1, there is less than 3% classification error for images with between 20% and 80% fracture surface, but there is more than 3% error for images with less than 10% or more than 90% fracture surface. This can be attributed to the fact that there is not enough of each of the three regions for the clustering algorithm to work properly.

5.2 Machine Learning Program Reliability

To evaluate the reliability of the K-mean algorithm for calculating fracture surface ratios, impact tests were conducted on an aluminum alloy and SM45C. Aluminum alloys produce mostly ductile fracture surfaces, and the actual penetration rate is less than 10%. However, the K-means algorithm calculates a brittle fracture surface ratio of about 80%. This is likely the result of the fact that the image of the fracture surface shows no distinction

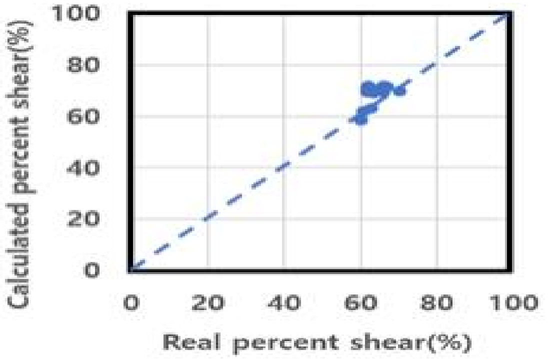


Fig. 10 Result of brittle fracture surface rate for SM45C by machine leaning program

Table 1 Raw data of the Comparison between Real Percent Shear and Calculated Percent Shear by K-means Algorithm (unit : %)

Real Percent Shear	10	20	30	40	50
Calculated Percent Shear	13.842	18.330	32.114	42.883	49.931
Real Percent Shear	60	70	80	90	-
Calculated Percent Shear	60.993	68.986	78.365	85.891	

between ductile and brittle fracture surfaces. Also, many ductile fracture surfaces represent another boundary. Further research is needed to modify the algorithm and program to handle materials with an imbalance of fracture types.

As shown in Figure 10, SM45C measured 12 fracture surfaces in the range of 13% with a ratio of 58% to 71%. The results of the program show calculations in the range of 10%, ranging from 60% to 70%. The margin of error was also about 9%.

6. Conclusion

The existing method of fracture surface ratio analysis of impact test specimens is time consuming and inaccurate[2]. A machine learning program written in MATLAB using the K-means algorithm automatically classifies the fracture surface data, saving time and excluding subjective judgements.

1. The program has been developed to classify fracture surface types and calculate the fracture surface ratio using the standard fracture ratio table.
2. The program classifies the background and the fracture surface in the first order, and the second classifies the background and the brittle and ductile.
3. If the fracture surface ratio is extremely high or low, the error in classification is large, apparently because in the case of extreme fracture surface rate, one area is rarely identified and cannot be classified.
4. In areas with less extreme fracture surface ratios (20-80%), we classify fracture types with less than 3% error.
5. The machine learning program classified SM45C impact fracture surfaces with about 9% error. Therefore, it is expected that the convergence of the material test field and the machine learning field will be possible in the future.
6. If a machine learning program can reliably classify fracture surfaces, it could be used to select materials for industrial equipment, especially for use in extreme environments.

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