Deep Learning based Dimple Detection for Quantitative Fractography

Ashish Sinha
Indian Institute of Technology Roorkee
Roorkee, India
asinha@mt.iitr.ac.in

K.S Suresh
Indian Institute of Technology Roorkee
Roorkee, India
ksuresh@mt.iitr.ac.in

Abstract

In this work, we try to address the challenging problem of dimple detection and segmentation in Titanium alloys using machine learning methods, especially neural networks. The images i.e. fractographs are obtained using a Scanning Electron Microscope (SEM). To determine the cause of fracture in metals we address the problem of segmentation of dimples in fractographs i.e. the fracture surface of metals using supervised machine learning methods. Determining the cause of fracture would help us in material property, mechanical property prediction and development of new fracture-resistant materials. This method would also help in correlating the topography of the fracture surface with the mechanical properties of the material. Our proposed novel model achieves the best performance as compared to other previous approaches. To the best of our knowledge, this is one the first work in fractography using fully convolutional neural networks with self-attention for supervised learning of dimple fractography, though it can be easily extended to account for brittle characteristics as well.

1. Introduction

Titanium is an important metal for making the plates of body armour of soldiers, body implants, surgical instruments. In addition, titanium alloys are also used for making aircrafts and spacecrafts due to it’s high strength and wear resistance [1] [7] [14].

Fracture patterns of metals in general and high-strength titanium and iron alloys in particular happens in a stage-like nature during deformation and stress accumulation. Deformation of metals caused due to application of load or corrosive actions of nature, causes an accumulation of pores predominantly in the central part of the neck of the fracture, which coalesce with grain (can be thought as domains in magnetic field) conglomerates leading to the growth of the crack in a continuous fashion in the direction of loading. Thus, the central crack which grows by thinning and breaking connections between the pores, together with the newly formed crack leaves traces on the surface in the form of dimples, which indicates the history of the material fracture [5] [15] [20].

![Stress-Strain curve](image)

Figure 1. Stress-Strain curve

The process of damage to a material can be depicted on stress-strain curve, whereas fracture is the final stage of deformation [1]. These links between the stages of deformation are important when analyzing the causes of fracture using fractographic analysis. Fractographic analysis uses physics of solid body, material science, optic-digital methods to determine the causes of fracture. Earlier, parameter measurements of fracture surfaces were made manually or automatically but the software was positioned by an operator. A large variety of materials made generalization difficult [2].

Administered by both the extrinsic (e.g. imposed loading, environmental conditions) and the intrinsic (microstructure) characteristics is the process of fracture of materials. The data regarding the affect of both intrinsic and extrinsic characteristics of the fracture process is contained in the surface of the fracture. Important means applied to study the surface of fracture is Fractography and obtain factors approaching to failure and data relating properties of material. To attain the topographic characterization of the surface, fractography is used. Analyzing and classifying the several mechanisms of fracture, and the interrelation-
ship between them with the microstructure of material, the situations approaching towards its failure, and its mechanical nature are also some applications in which fractography plays its part.

Formation of dimples on the fracture surface is due to the ductile fracture of materials. Generally, the micro-pore merger in the material during deformation in plastic region leads to such dimples. After effect of the pore rupture and the destruction of the surrounding material are Dimples as shown in Figure 2. Many models of nucleation, growth, and coalescence of pores are known and their application under the uncertain fracture of materials usually results as complicated. Determination of a number of parameters of the material by the demand for laboratory.

The ponderous process which is quantitative and qualitative assessment of fracture surface. Executed manually by experienced and well trained technicians, hence requiring significant labour. Quantitative estimations are likely to have more errors because there is a huge dependency on human factor.

In previous works, the authors proposed methods for fractographic recognition, control and calculation of parameters of the dimples of based on neural networks [17] [19]. In [18], the authors trained 17 models of neural networks with various sets of hyperparameters, then their speed and accuracy were evaluated and the optimal neural network was selected. We propose a fully convolutional uNet [21] based deep neural network with position and channel based attention residual blocks [22] and squeeze and excitation [11] block in the bottleneck layer for the detection of deep dimples and counting for calculating the fracture tendency of the metal i.e. titanium.

2. Related Work

In the last century, metallurgists and material scientists have acquired, analysed and compared images of microstructures in a progressive way. Most of the effort was put in to learn a defined material system and different classes of microstructures. If the features of micro structures are known then digital analysis techniques on images would be helpful in characterising, segmenting and comparing different structures with high resolution. Currently the analytics of microstructures is mostly focused on finding the relationship between structure and properties by using the shape and size and appearance of the features. These approaches have move forwarded to more of a machine learning approach where the properties are found out by the choosing correct algorithms. Some of the areas where machine learning techniques are used in metallurgy and materials science are: New material Design Material, Property Prediction, Microstructure recognition, and analysis of failure etc.

2.1. Computer Vision in Quantitative Fractography

The main interest in fractography is due in finding the correlation between the features of the surface that is fractured and the environment or conditions that lead to its failure. For centuries, this has remained qualitative in nature. Mostly, scientists examine the SEM, OPM images of samples for failure analysis. Therefore quantitative analysis brings the potential for improving and understanding the mechanisms that control the fracture process and also determine the reliability of the models that in the current material design system. The latest advancement in the field of image analysis and moreover the availability of machine learning tools, it has become more easy to automate the event of finding important features and information from the fractographs.

The use of computer vision methodologies by [4] lead to identify the images which contained dendritic morphology to classify if the the direction was longitudinal or transverse. Another use case has been automatic measuring the volume of ferritic(iron) volume fraction from the binary phase structures of ferritic and austenite(a phase of iron). In the field of fractography, many successful attempts have been made to build automated models for quantitative fractography [2] used non-linear algorithms of machine learning (ANN and SVM) and combined it with texture analysis to classify the images into there modes: ductile sudden, brittle sudden and fatigue. A recent work [22] aims to quantify fracture surface for materials with brittle fracture characteristics. Our work focuses on ductile materials.

In our project we use different types of neural networks to detect dimples in ductile fracture materials on SEM images of titanium alloys which can be further used to find the properties of fracture mechanism.

Our work explores the application of deep learning methods in fractography, an active field of research in material science. Below, we briefly explain the terms necessary to better understand our work.
2.2. Fractography

Fractography is a technique to understand the causes of failures and also to verify theoretical failure predictions with real life failures. It can be used in forensics, for analyzing broken products which have been used as weapons, such as broken bottles. Thus a defendant might claim that a bottle was faulty and broke accidentally when it impacted a victim of an assault. Fractography could show the allegation to be false and that considerable force was needed to smash the bottle before using the broken end as a weapon to deliberately the victim. In these cases, the overall pattern of cracking is important in reconstructing the sequence of events, rather than the specific characteristics of a single crack, since crack grows by coalescing with other grains in the microstructure of the metals.

2.3. Crack Growth

The initiation and continuation of crack growth is dependent on several factors such as bulk material properties, geometry of the body, geometry of the crack, loading rate, loading distribution, load magnitude, environmental conditions, time and microstructure. Cracks are initiated, and as the cracks grow, energy is transmitted to the crack tip at an energy release rate \( G \), which is a function of the applied load, crack length and the geometry of the body. All solid materials, have an intrinsic energy release rate \( G_C \), where \( G_C \) is referred to as the fracture energy or fracture toughness of the material. A crack will grow if \( G \geq G_C \).

2.4. Microstructure

Microstructure is a very small scale structure of a material, defined as the structure of a prepared surface of a material as revealed under an optical microscope above 25x magnification. The microstructure of a material correlates strongly with the strength, toughness, ductility, hardness, wear resistance, etc of the material. A microstructure’s influence on the physical and mechanical properties of a material is governed by the different defects present or absent in the structure. These defects can take many forms but the primary ones are the pores. To acquire micrographs, both optical as well as electron microscopy is used.

2.5. Dimple Fracture

A dimple fracture is a type of material failure on a metal’s surface that is characterized by the formation and collection of microvoids along the granular boundary of the metal i.e. the fracture path. The occurrence of dimple fractures is directly proportional to increased corrosion rates. The material appears physically dimpled when examined under high magnification. There are three main types of dimple fractures:

- Shear fractures
- Tearing fractures
- Tensile fractures

All three of these fractures are characterized by tiny holes, known as microvoids, which are microscopically located in the interior of a piece of metal when under the force of an external load. The greater the load, the greater the proximity and the total gap volume of these voids. The appearance of such a fractured surface is referred to as a dimple rupture. A scanning electron microscope can be used to examine a dimple rupture at a magnification of about 2500x.

3. Methodology

Here we discuss the fractographic analysis for detection of dimples in fracture metal surfaces using various deep learning models. We consider Titanium alloys as our focus of discussion. The techniques used for detection of dimples in Ti samples and fractographs have been briefly discussed below.

3.1. U-Net

The U-Net [21] is mainly employed for bio-medical image segmentation. It has two parts: a contracting encoder and an expanding decoder. The encoder, a feature correction path, is a continuous stack of Conv and MaxPool layers; used for image identification. The decoder, a feature expanding path, is used for collecting exact localisation of fractures using transposed convolutions or deconvolutions. The model is an end-to-end fully convolutional network. The image of any size can be fed in the model as it lacks any densely connected layer.

3.2. U-Net++

This Model uses Dense block ideas of DenseNet [12] to improve upon U-Net [21]. The original U-Net lacked the following features, which had now been incorporated in U-Net++:
It has convolution layers in skip pathways that acts as a connecting link between the semantic gap of decoder and encoder feature maps.

It has dense skip connections on skip pathways for improving the gradient flow.

The construction of the model begins with an encoder sub-network and a decoder sub-network after it. Skip pathways connecting the encoder and decoder have been depicted in green and blue. The deep supervision has been depicted using red.

The example in the figure above exhibits feature map travel through the top skip pathway.

The skip pathway between nodes $X_0, 0$ and $X_1, 3$, as shown in the figure comprises three convolution layers and a deep dense convolution block.

A convolution layer follows every concatenation layer. This convolution layer considers output from preceding convolution layers of the dense block and upsampled output from lower dense block, and fuses them.

The high resolution feature maps at multiple semantic levels are possible because of the nested skip pathway. Due to the nested skip pathway, it generates high resolution feature maps at multiple semantic levels. Thus, the loss has estimated from four semantic levels.

3.3. Mask R-CNN

Mask R-CNN [9] is the skeletal that assists in object detection and localization. It completes the task in two steps: scanning the image and generating proposals to point the probable locations of an object, classification on first step proposals, and generation of bounding boxes and masks.

3.4. Proposed Model

Like the U-Net architecture, our proposed network is divided into two parts, a contracting encoder and an expanding decoder. For the encoder part, we employ 5 layers of residual convolutional blocks with channel and spatial attention as proposed in [8] but instead of using attention blocks in parallel we find that using them as proposed in [23] gives better results in our case. We employ a dense connection [12] in each residual block used in the encoder of the model. Bottleneck blocks consists of 3 layers of dense connection of residual convolution blocks followed by a squeeze and excitation block [11]. The encoder part starts with a convolution of filter size 5 and stride 1 followed by batchnorm [13] and relu activation. The other convolutions have a filter size of 3.

In the decoder part, we make use of the residual convolutional blocks like mentioned in the encoder part and use parameter-free bilinear upsampling instead of transposed convolutional operations to reduce the number of trainable parameters [5]. The overall model architecture is shown in the figure. Each upsampling block is followed by a channel and spatial attention block.

The goal of this work is not to propose a novel architecture but to establish a baseline for further development and also to show the application of deep learning models on an age old problem of dimple detection for quantitative fractography so as to determine the cause of fracture in materials which in turn will lead to the design of new and better materials.

4. Evaluation

4.1. Dataset

For conducting our experiments, we collected 2216 high-resolution SEM images of Ti alloys at 200x, 500x, etc magnification. It is a very difficult process to obtain this kind of data in such magnitude since it requires heavy preprocessing of the metal surface before it can be viewed under a scanning electron microscope. With the help of our supervisor, we performed the tedious task annotating the dataset with deep dimples, which was then cropped into
Figure 5. Our Proposed model

slices of 128x128px size to generate around 221586 images, which is popular in medical imaging involving whole-scale images (WSI) or satellite imagery. We used around 70% the total images for training our model, 20% for validating our model and 10% of the dataset was reserved for testing our model.

We shall open-source the model and dataset once this work is accepted.

4.2. Experiments

In the experiments, we observed that training the model for a total 150 epochs was enough to reach convergence. The input dimensions of the image was 128x128 and the output dimension was also 128x128. We used Adam [16] optimizer with a learning rate of $1e^{-4}$ and a weight decay $1e^{-6}$. We use an exponential decay for learning rate after every 10 epochs. We evaluate our model on the basis of dice score [6] and compare it to other state-of-the-art methods.

$$\text{Dice Score (DSC)} = \frac{2|A \cap B|}{|A|+|B|}$$

4.3. Results

We evaluate the performance of our proposed model and the baseline model on the widely used metric of Dice-coefficient. The results of various methods are tabulated in Table 1. It’s visible from the quantitative and qualitative results [7][8] that our proposed model performs the best as compared to other previous established methods. After getting the segmentation results, the results can be analyzed to understand the morphology of the fracture surface as to calculate the fracture tendency of the metal. Depending on the amount of deep dimples or shallow dimples (beyond the scope of this work) present in the image, we can predict if the material underwent brittle or ductile fracture. This work thus, aims to reduce the time and effort of material science researchers for fractographic analysis.

| Method                        | Dice Score (DSC) |
|-------------------------------|------------------|
| U-Net                         | 0.68509 (±7.88%) |
| U-Net++                       | 0.73423 (±6.51%) |
| Attentive U-Net               | 0.81630 (±5.27%) |
| ResU-Net with Dual Attention (ours) | 0.86305 (±5.05%) |

Table 1. Quantitative Results on Microstructures of Ti alloys

5. Conclusion

In this work, we have elucidated how fractures occur in the material and how they can be fatal while in service. We have presented an overview of the traditional as well as modern approaches involved in detecting of these defects
on the microscopic scale. We also present new methods for deep dimple detection, which may serve as the first step towards categorizing the type of defect a material had, the likelihood of occurring of such defects can be further calculated by computing the area of dimples. This work presently focuses on dimple detection for ductile materials like Ti alloys, which can be easily extended to other kinds of defects and other materials too. This is a robust method, which has further room for improvements. This work is an aim to foster machine learning and deep learning principles in automating the traditional methods applied in material science for fractography. We hope to see better models in the future which can lead to reduced human labour and material wastage, increased efficiency during production of new materials.

References

[1] Hooyar Attar, Mariana Calin, LC Zhang, Sergio Scudino, and Jürgen Eckert. Manufacture by selective laser melting and mechanical behavior of commercially pure titanium.
[2] MX Bastidas-Rodriguez, FA Prieto-Ortiz, and Edgar Espejo. Fractographic classification in metallic materials by using computer vision. *Engineering Failure Analysis*, 59:237–252, 2016.

[3] CD Beachem and GR Yoder. Elastic-plastic fracture by homogeneous microvoid coalescence tearing along alternating shear planes. *Metallurgical Transactions*, 4(4):1145–1153, 1973.

[4] Aritra Chowdhury, Elizabeth Kautz, Bülent Yener, and Daniel Lewis. Image driven machine learning methods for microstructure recognition. *Computational Materials Science*, 123:176–187, 2016.

[5] Jeffrey De Fauw, Joseph R Ledsam, Bernardino Romera-Paredes, Stanislav Nikolov, Nenad Tomasev, Sam Blackwell, Harry Askham, Xavier Glorot, Brendan ODonoghue, Daniel Visentin, et al. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature medicine*, 24(9):1342–1350, 2018.

[6] Lee R Dice. Measures of the amount of ecologic association between species. *Ecology*, 26(3):297–302, 1945.

[7] Shima Ehtemam-Haghighi, KG Prashanth, Hooyar Attar, Anil K Chaubey, GH Cao, and LC Zhang. Evaluation of mechanical and wear properties of ti6nb7fe alloys designed for biomedical applications. *Materials & Design*, 111:592–599, 2016.

[8] Jun Fu, Jing Liu, Haijie Tian, Yong Li, Yongjun Bao, Zhiwei Fang, and Hanqing Lu. Dual attention network for scene segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3146–3154, 2019.

[9] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.

[10] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[11] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 7132–7141, 2018.

[12] G Huang, Z Liu, KQ Weinberger, and L van der Maaten. Densely connected convolutional networks. arxiv 2017. *arXiv preprint arXiv:1608.06993*.

[13] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, 2015.

[14] Igor V Kabashkin and Irina V Yatskiv. Reliability and statistics in transportation and communication. 2010.

[15] GA Kardomateas. Fractographic observations in asymmetric and symmetric fully plastic crack growth. *Scripta Metallurgica*, 20:609–614, 1986.

[16] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2014.

[17] Igor Konovalenko, Pavlo Maruschak, Olegas Prentkovskis, and Raimundas Junevičius. Investigation of the rupture surface of the titanium alloy using convolutional neural networks. *Materials*, 11(12):2467, 2018.

[18] Pavlo Maruschak, Ihor Konovalenko, Mykola Chausov, Andrii Pylypenko, Sergey Panin, Ilya Vlasov, and Olegas Prentkovskis. Impact of dynamic non-equilibrium processes on fracture mechanisms of high-strength titanium alloy vt23. *Metals*, 8(12):983, 2018.

[19] E Merson, V Danilov, D Merson, and A Vinogradov. Confocal laser scanning microscopy: The technique for quantitative fractographic analysis. *Engineering Fracture Mechanics*, 183:147–158, 2017.

[20] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[21] Stylianos Tsopanidis, Raúl Herrero Moreno, and Shmuel Osowski. Toward quantitative fractography using convolutional neural networks. *Engineering Fracture Mechanics*, 231:106992, 2020.

[22] Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon. Cbam: Convolutional block attention module. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 3–19, 2018.