Scripta Materialia 113 (2016) 101–105

Contents lists available at ScienceDirect

Scripta Materialia

journal homepage: www.elsevier.com/locate/smm

Systematic and objective identification of the microstructure around damage directly from images

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ARTICLE INFO

Article history:
Received 2 September 2015
Received in revised form 29 September 2015
Accepted 3 October 2015
Available online 31 October 2015

Keywords:
Microstructure
Morphology
Damage
Multi-phase materials
Image processing

ABSTRACT

An original experimental approach is presented to automatically determine the average phase distribution around damage sites in multi-phase materials. An objective measure is found to be the average intensity around damage sites, calculated using many images. This method has the following benefits: no phase identification or manual interventions are required, and statistical fluctuations and measurement noise are effectively averaged. The method is demonstrated for dual-phase steel, revealing subtle unexpected differences in the morphology surrounding damage in strongly and weakly banded microstructures.

1. Introduction

Multi-phase materials typically consist of multiple phases with distinct mechanical and physical properties. Their fracture behavior is only partially understood, as the morphology – often complex – plays a crucial role (e.g. in multi-phase metals [1], concrete [2], and geophysics [3]). Experimental approaches towards systematic characterization of the microstructural morphology in damaged regions are cumbersome, whereas a reliable methodology might yield new insights and more accurate input for (macroscopic) damage models [4–6].

Different statistical descriptors have been developed for arbitrary (microstructural) morphologies. Well known examples are the two-point probability or auto-correlation function and the lineal path function [7,8]. For an isolated inclusion phase (e.g. spherical particles) additional descriptors have been developed that convey more information, such as the two-point cluster function and the radial distribution function [9]. Almost all measures however require explicit knowledge of the spatial distribution of phases. This knowledge is difficult to obtain experimentally and requires extensive manual processing as the contrast between the phases is often low [10]. Furthermore, they are aimed at the quantification of the distribution and/or size of a single phase, while a conditional probability is needed to characterize the neighborhood of a phase (e.g. morphology around damage).

In a recent numerical study, De Geus et al. [11] characterized the spatial correlation between damage and phase distribution by calculating the average arrangement of phases around damage sites. Extending this analysis to an experimental setting faces the problem that [11] considered equi-sized grains in the model, corresponding to a finite set of discrete positions (distance measures) that coincide with the grains. In reality the position is continuous (finely discretized experimentally through digital images) and the grains are irregular in position and shape. Furthermore the interpretation in [11] made use of the explicit knowledge of the phases and damage as a function of the position, not available experimentally.

This letter presents a methodology to quantify the conditional spatial correlation between a uniquely identified feature (e.g. damage) and its surrounding morphology directly from a micrograph, without the need for an explicit description of the microstructure. As a proof of principle the average arrangement of martensite and ferrite around damage in a dual-phase steel microstructure is characterized. It is well known that in commercial grades martensite often presents a banded structure, which has a strong influence on the damage [1]. Two different grades of steel are therefore compared that evidence strongly and weakly banded martensite. Tensile tests on these steel grades show that the weakly banded microstructure has a lower fracture strain, which is in disagreement with the common understanding. The proposed analysis provides novel insights into this topic.

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http://dx.doi.org/10.1016/j.scriptamat.2015.10.007
1359-6462/

2. Technique

The spatial correlation analysis[1] is discussed in detail in this section, using an artificial example for which the average distribution of two phases around damage sites is quantified based on an image. Several aspects have to be carefully considered to obtain statistically meaningful results. To simplify notation, the analysis is based on fields that are discretized in space.

Consider the example in Fig. 1(a), which shows part of a periodic microstructure comprising two phases: circular inclusions (white) embedded in a matrix (gray). The inclusions have been numerically generated by randomly perturbing the size and position of an initially regular grid of equi-sized circles with diameter $2\bar{R}$. Damage (black) is mimicked by shifting each inclusion to the right, applying a position perturbation, and shrinking it by a factor two. These dimensions are indicated in the zoom next to Fig. 1(a). Two fields are used to describe this image: the image intensity $\mathcal{I}$ and the damage indicator $\mathcal{D}$. For this example $\mathcal{I}(\vec{x}_i) = 1$ in the inclusion phase (white), $\mathcal{I}(\vec{x}_i) = 1/2$ in the matrix (gray), and $\mathcal{I}(\vec{x}_i) = 0$ in damage (black). The damage indicator $\mathcal{D}(\vec{x}_i) = 1$ inside the damage (black) and is zero elsewhere. The position $\vec{x}_i$ denotes the position of a pixel, taken at the position (i, j) in the pixel matrix.

The phase probability $\mathcal{P}$ around damage is calculated as the weighted average

$$\mathcal{P}\left(\Delta\vec{x}\right) = \frac{\sum_i \mathcal{W}\left(\vec{x}_i\right)\mathcal{I}\left(\vec{x}_i + \Delta\vec{x}\right)}{\sum_i \mathcal{W}\left(\vec{x}_i\right)} \tag{1}$$

where the weight factor $\mathcal{W}(\vec{x}_i) = \mathcal{D}(\vec{x}_i)$ for this example. The spatial average is obtained by looping over all pixels i (optionally excluding a boundary region of half the dimensions of the region-of-interest). It thus corresponds to the normalized discrete *convolution* between $\mathcal{W}$ and $\mathcal{I}$. The result is the expectation value of the intensity, $\mathcal{P}$, at a certain position $\Delta\vec{x}$ relative to the damage site. It scales with the image contrast. In the limit case that $\mathcal{I}$ and $\mathcal{W}$ are separate fields that are both explicitly known (i.e. zero or one), $\mathcal{P}$ is the probability to find $\mathcal{I}$ at a certain position relative to $\mathcal{W}$.

The analogy of $\mathcal{P}$ with a probability allows the interpretation of its value based on simple statistical arguments. If there is no correlation between $\mathcal{I}$ and $\mathcal{W}$, then $\mathcal{P} = \bar{\mathcal{I}}$, with $\bar{\mathcal{I}}$ the spatial average of $\mathcal{I}$. If, at a position $\Delta\vec{x}$ relative to the damage site, more inclusion phase is found than its spatial average, then $\mathcal{P}(\Delta\vec{x}) > \bar{\mathcal{I}}$ and vice versa.

For the example the result is shown in Fig. 1(b), where the colormap recovers the extremes (black and white) of the image. Directly to the left of the center (where the damage is) $\mathcal{P} \gg \bar{\mathcal{I}}$, i.e. the inclusion phase is identified there. Directly around the center, in all other directions, $\mathcal{P} \approx 0$ which corresponds to damage (black in the image). At larger distance, $\mathcal{P} < \bar{\mathcal{I}}$ corresponding to predominantly matrix phase. Several lighter regions indicate a long-range correlation between damage and inclusion, an intrinsic property of the example for which the inclusion positions are not random but a random perturbation of an initially regular arrangement.

The most obvious artifact in this result is that directly around the damage in the center, damage is identified in a region that corresponds to the size of the damage sites, $\bar{R}$. As the goal is to identify the phase around damage, this cross-correlation of damage should be avoided. It is accounted for through a mask $\mathcal{M}$, which is defined such that $\mathcal{I}(\vec{x}_i)$ is ignored for all pixels where $\mathcal{M}(\vec{x}_i) = 0$. To remove "damaged" pixels $\mathcal{M}(\vec{x}_i) = 1 - \mathcal{D}(\vec{x}_i)$. The average phase around damage is now:

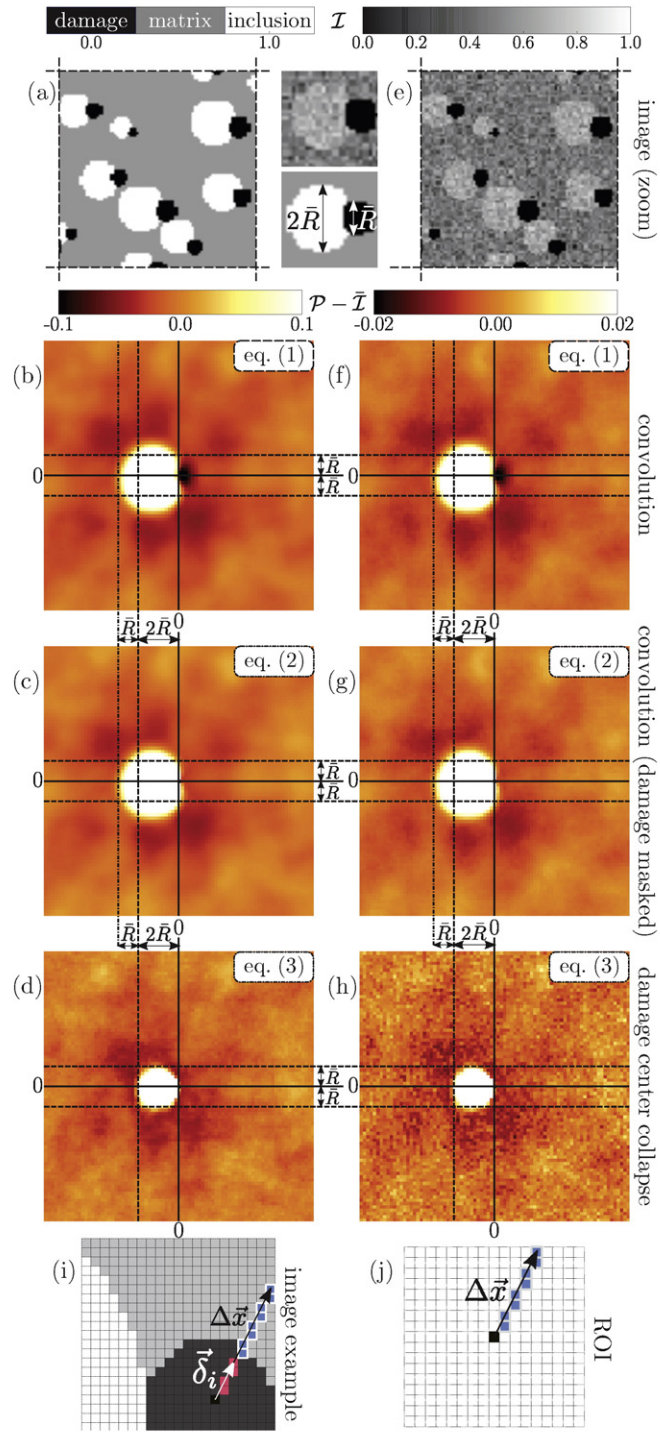

Fig. 1. Virtual experiment in the ideal setting: no noise and high phase contrast (a–d), and the realistic setting: with noise and low phase contrast (e–h). From top to bottom: (a,e) the two-phase microstructure, (b–h) the average phase arrangement around a damage site calculated in three different ways. (i–j) An illustration of Equation (3), used in (d,h).

$$\mathcal{P}\left(\Delta\vec{x}\right) = \frac{\sum_i \mathcal{W}\left(\vec{x}_i\right)[\mathcal{I}\mathcal{M}]\left(\vec{x}_i + \Delta\vec{x}\right)}{\sum_i \mathcal{W}\left(\vec{x}_i\right)\ \mathcal{M}\left(\vec{x}_i + \Delta\vec{x}\right)} \tag{2}$$

where the mask in the numerator ensures that the contribution of $\mathcal{I}$ in the damaged areas is omitted, and the mask in the denominator corrects

[1] The implementation is open-source. It is optimized, applicable to large sets of high resolution images (https://tdegeus@bitbucket.org/tdegeus/gooseeye.git and http://www.geus.me/gooseeyewww.geus.me/gooseeye).