Microscopic Texture Components Classification for Image Segmentation

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Abstract

This paper presents the use of the sliding window technique for texture feature extraction in order to identify regions of interest in microscopic images of aluminium alloys. Our goal is to automate experimental evaluation of high-temperature sustainability of such alloys of various composition. The study includes the comparison of selected feature extraction methods within the space, frequency and space-scale domains using namely space-based statistics, the discrete Fourier transform (DFT), and the discrete wavelet transform (DWT) for features computation. The compactness of feature clusters is evaluated exploiting a chosen numerical criterion to determine the most suitable way of features computation and to compare the resulting features from the three different domains. For real images, the clusters compactness can often be improved by preprocessing methods such as smoothing. In this paper, we employ median filtering and wavelet shrinkage and observe their effect on the results.

1. Introduction

Aluminium alloys (Al-Cr-Fe-Ti-Ce)

- Favorable properties: low density → widely used in the automotive and aerospace industries.
- Usage limitation: high-temperature resistance only up to 200°C
- With an optimal admixture of cerium (Ce), the alloy obtained by fast cooling sustains temperatures up to 400°C.
- The degree of high-temperature resistance is observed on annealed alloy samples of different Ce content using the electronic microscope. (To a certain point, homogeneous texture becomes coarser.)

Project goal

- Detect the homogeneous and the coarser-texture areas in order to automatically evaluate the degree of temperature degradation.

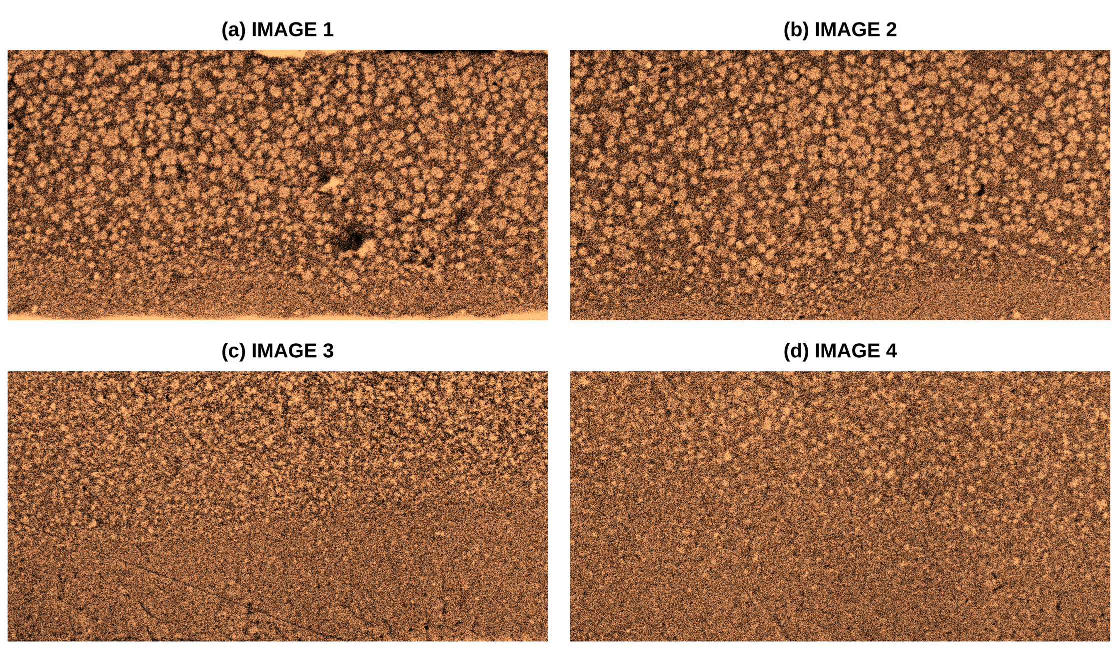


Fig. 1. Microscopic images of aluminium alloys samples with areas of coarser texture caused by annealing (image histograms are equalized)

2. Texture Features Extraction

As an input, the classification process requires a pattern matrix $\mathbf{P}_{R,Q}$ containing $R=2$ features extracted using a sliding window $\{I_k\}_{k=0}^{Q-1}$ of the size 64×64 pixels.

Methods of features computation [5]

- *Space-based features*
  1. The median
  2. The standard deviation
- *DFT-based features* [3]
  1. The mean square magnitude of the low-frequency coefficients from the interval $\langle 0; F_s/4\rangle$ in 2 dimensions
  2. The mean square magnitude of the high-frequency coefficients from the interval $\langle F_s/4; F_s/2\rangle$, where F_s is the sampling frequency
- *DWT-based features* [1]
  1. The mean of square values of the scaling coefficients form level 3
  2. The median of square values of the diagonal wavelet coefficients from level 3 (bior4.4 wavelet)

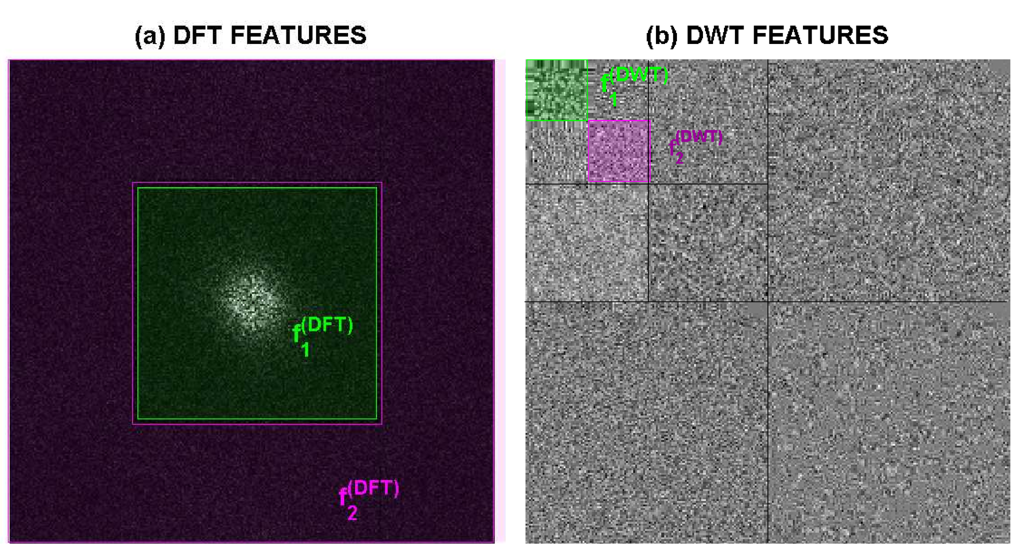


Fig. 2 Coefficients exploited for features computation presenting **(a)** highlighted DFT magnitudes groups and **(b)** highlighted DWT coefficients subbands (re-normalized for better visibility)

3. Smoothing

Two chosen smoothing methods

- Median filtering (convolution with a 7×7 mask)
- Wavelet shrinkage (2 levels, bior4.4 wavelet)

The wavelet shrinkage algorithm

- Additional noise model of a noisy wavelet coefficient observation

$$w(k) = y(k) + n(k) \quad (1)$$

where $y(k)$ and $n(k)$ correspond to the wavelet coefficients of a noise-free signal and iid Gaussian noise, resp., for $k = 0, 1, \ldots, N-1$.

- MAD estimate of the standard deviation for iid Gaussian noise

$$\hat{\sigma} = median(\,|w_1^d(0)|, |w_1^d(1)|, \ldots, |w_1^d(N_1-1)|\,)\ /\ 0.6745 \quad (2)$$

where $\{w_1^d(k)\}_{k=0}^{N_1-1}$ are the diagonal wavelet coefficients of level 1

- Global penalized threshold δ by Birge-Massart [4] is computed by minimizing the criterion

$$crit(t) = -\sum_{k=0}^{t} w(k)^2 + 2\,\hat{\sigma}^2\, t\ (\alpha + \log N\ /\ t) \quad (3)$$

where $\alpha \in \{\mathbb{R} > 1\}$ is a tuning parameter for the penalty term (in this work $\alpha = 1.5$) and $\{w(k)\}_{k=0}^{N-1}$ are the wavelet coefficients sorted in decreasing order of their absolute value. For t^* minimizing the criterion, the threshold value is given by $\delta = |w(t^*)|$.

- Soft thresholding to estimate values of the wavelet coefficients $y(k)$ of the noise-free signal

$$\hat{y}(k) = \begin{cases} sign\{w(k)\}\cdot(|w(k)| - \delta) & for\ \ |w(k)| > \delta \\ 0 & otherwise \end{cases} \quad (4)$$

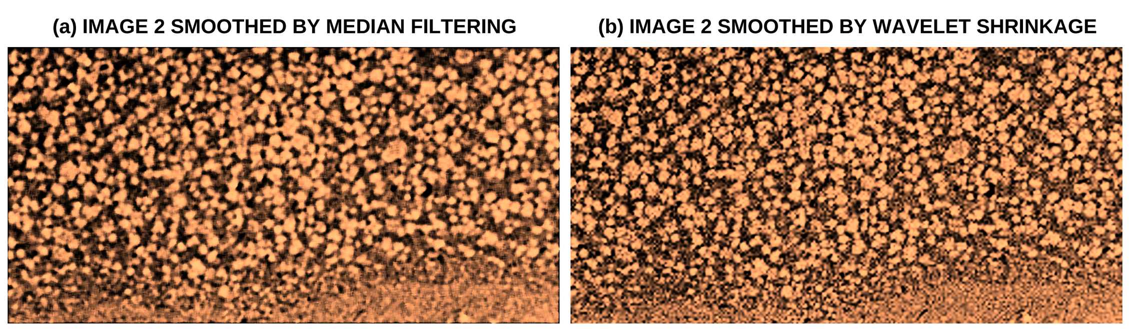
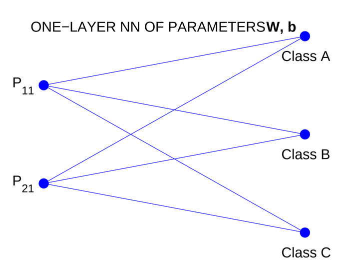


Fig. 3 Smoothing of image 2 presenting the results of **(a)** median filtering and **(b)** wavelet shrinkage

4. Classification

Classification using self-organizing neural networks [2]



- Classification of Q segments using R features organized in the pattern matrix $\mathbf{P}_{R,Q}$
- The number of classes S equals the number of output layer elements
- The training process
  - The weights matrix $\mathbf{W}_{S,R}$ is recursively recalculated to minimize the distances between each input vector and the corresponding weights of the winning neuron (with coefficients closest to the current pattern)
  - Successful when the network weights belonging to separate output elements represent typical class individuals

The Cluster Segmentation Criterion (CSC) [6]

- Each class $i = 1, 2, \ldots, S$ comprising N_i-segments is characterized by the mean Euclidean distance *Dist* of the column feature vectors $\mathbf{p}_{j_k}$ of class segments j_k for $k = 1, 2, \cdots, N_i$ from the class center in the i-th row of matrix $\mathbf{W}_{S,R} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_S]'$ by relation

$$ClassDist(i) = \frac{1}{N_i}\sum_{k=1}^{N_i} Dist(\mathbf{p}_{j_k}, \mathbf{w}_i) \quad (5)$$

- The mean value of average class distances divided by the mean value of class centers distances

$$CSC = mean(ClassDist)\ /\ mean(Dist(\mathbf{W}, \mathbf{W}')) \quad (6)$$

- Evaluates the classification process giving low values for compact and well separated clusters and high values for close and dispersed clusters

5. Results

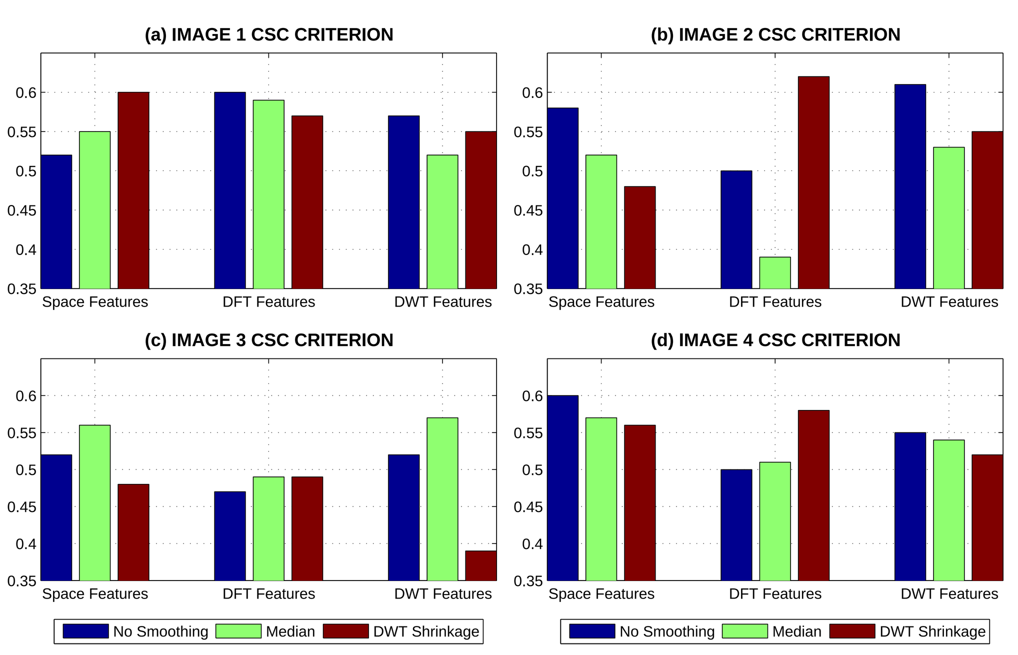


Fig. 4 Classification results according to the *CSC* criterion using different smoothing and feature extraction methods for **(a)** image 1, **(b)** image 2, **(c)** image 3, and **(d)** image 4.

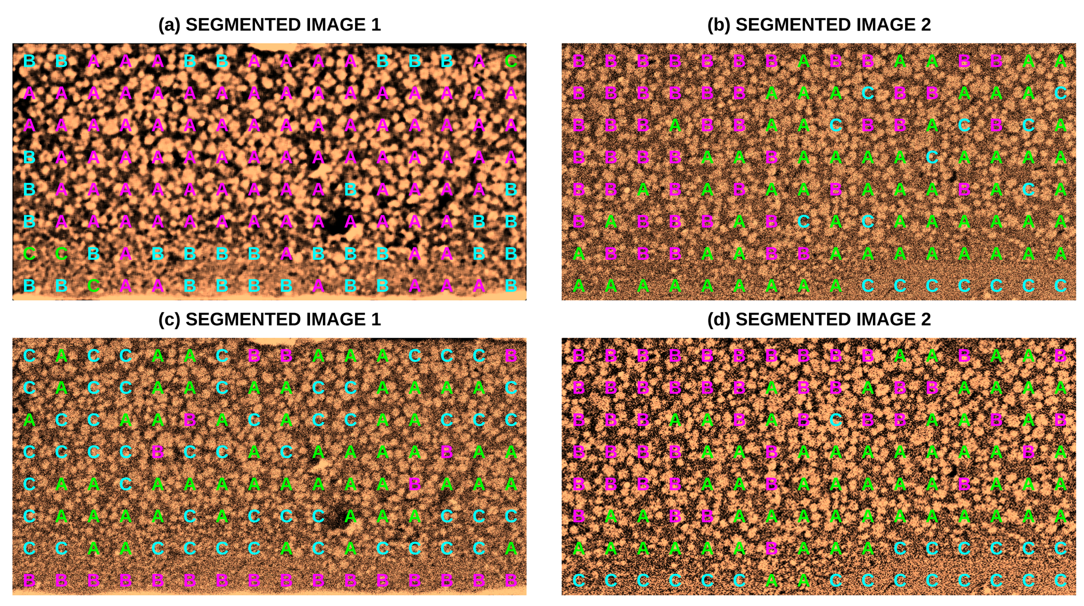


Fig. 5 Segmentation results for two different alloy samples using **(a)** the frequency-based features extracted from image 1 smoothed by median filtering,**(b)** the space-based features from image 2 without smoothing, **(c)** the wavelet-based features from image 1 without smoothing, and **(d)** the space-based features from image 2 smoothed by wavelet shrinkage

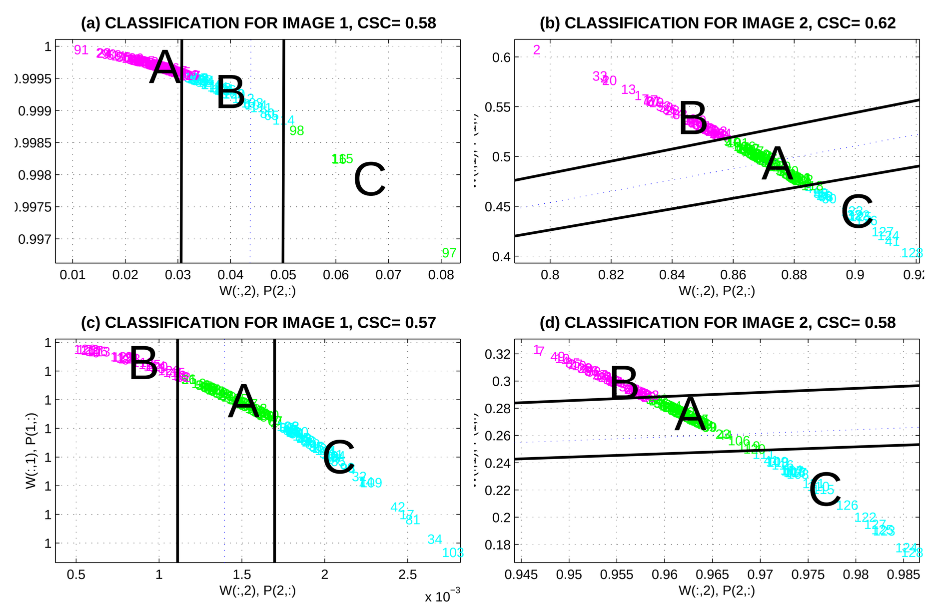


Fig. 6 Clustering and classification of computed features corresponding to the segmentation results in Fig. 5 in respective order and including evaluation by the *CSC* criterion

6. Conclusions

The proposed region detection algorithm is based upon feature extraction using the sliding window and subsequent classification using an artificial neural network. Considering the data properties, we produce three different feature computation methods based on the space, frequency, and wavelet domain. According to the *CSC* measure of clusters quality and visual evaluation of the segmentation results, the DWT and DFT features after smoothing slightly surpass the other methods. Wavelet shrinkage smoothing surpasses median filtering in the positive effect on the segmentation results except when in combination with DFT features.

Future work

- Use overlapping windows
- Improve image quality (locally varying sharpness, scratches)
- Search for the most efficient combination of features and smoothing methods
- Evaluate the percentage of successfully classified segments
- More experiments

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