Antal Kerpely Doctoral School of Material Science and Technology

Eutectic morphology description by automatic computer aided image analysis

Thesis book

by
Kornél Bortnyik

Supervisor:
Dr. Péter Barkóczy

Institute of Physical Metallurgy, Metal Forming and Nanotechnology Faculty
of Material Science and Engineering
University of Miskolc
Hungary
2022

Introduction

The development of computer technology has brought change in our lives in several areas. Neumann computers have become part of our everyday lives. Advanced image processing algorithms have also appeared in the software used every day, such as: face recognition, the so-called OCR, or optical character recognition, allows a computer to interpret photographed text as text. Pattern recognition algorithms are widely used in medicine for computer image analysis of tissue images. The advent of high-resolution and fast imaging devices has made it possible to create computer vision, where computers process the perceived image and, as a result, interfere with the observed processes. In material engineering practice, we can encounter computer image analysis during metallographic examinations. One of the classic methods of material classification is metallographic examination, in which the microstructure of metals is examined using an optical microscope. The microstructure of materials significantly affects their properties. Therefore, microstructure testing has become an effective tool for material qualification procedures. When examining the microstructure, a variety of questions can arise: What phases can be seen in the image? What is their area fraction? What is their shape? What is their distribution in the microstructure? etc These questions have previously been answered by comparison with reference images and / or by performing simple measurements. However, for these measurements, respectively the comparison required experienced professionals and the outcome of the evaluation depended heavily on their professional qualifications and experience. The use of computer image analysis systems for today's evaluation largely eliminates these problems, but it is still necessary to employ professionals with both IT and metallographic knowledge to properly evaluate the images. The person performing the evaluation must be familiar with the steps and possibilities of computer image analysis and be able to evaluate the results obtained.

Today, we have reached another turning point in the history of industrial revolutions.

The previous one was the advent of computers and automation, the current one is the advent of smart factories. Smart devices mean that artificial intelligence is already working in the applied algorithms, and the devices are also able to communicate with their environment, i.e. human intervention is displaced.

Automatic computer image analysis

Implementing automated computer image analysis requires methods that can completely eliminate the need for human intervention. In order to evaluate a large number of samples in the right quality, it is inevitable to use automatic computer image analysis. However, for this to be effectively accomplished, an algorithm must be developed whose only condition is that the input image be a microscopic image of eutectic sample.

In computer image analysis, the cell automaton is not unknown, as we encounter it in many solutions, although it is not always presented in this way. The convolutional operations used in image analysis are total cellular automata. The digital grayscale image can be considered of as a universe of cells with a square geometry. The cells are the pixels. The size of the universe is equal to the size of the image. Cell states can be an integer in the range 0 – 255 for an 8-bit image. Similar to grayscale morphological transformations, binary morphological transformations are also deterministic cellular automata. However, in this case, the automaton has only two states. Performing the transformation once corresponds to a cellular step in every case. Nowadays, a stochastic cellular automaton is used in computer image analysis, although it is not widely used. As can be seen, the representation of the image itself makes the application of the cellular automata efficient, so in my development I tried to answer the questions raised only by using a cellular automaton.

Automatic correction of uneven background illumination

Uneven backlighting significantly hinders measurements on images, as this error complicates the segmentation operation. On images with such an error, automatic segmentation algorithms without arguments do not work properly. All this means that human intervention is required during segmentation, which would interrupt the process of automatic image analysis. Therefore, it is necessary to correct this error. The method I chose to correct the backlight is based on the *Lava-flow* algorithm, which is used to predict the direction of lava flows, and is still in the development stage. Another image does not need to use this procedure, just need the existing one to fix it. It is also based on a cellular automaton, just in this case - since we are still working with a grey image - it means an automaton with 256 states. After scanning the image, the position and value of the maximum brightness area are determined, and then the cellular automata start working. When defining the area, the image is first quartered, then the brightest is selected, and the brightest is quartered again and the brightest is selected. This will continue until the area is 34 pixels in size. The boundary conditions are then defined, which in this case means that the two sides rows of pixels in the image are made equal to each other. This is followed by a grey closure on the side two pixels rows, and then I replace the image within the border pixel rows with the maximum brightness pixel value. In each step, the cellular automaton performed an operation that can be written with the following formula:

$$PA_{i,j} = PA_{i,j} + A \cdot (PA_{i+1,j} + PA_{i-1,j} + PA_{i,j-1} + PA_{i,j+1} - 4 \cdot PA_{i,j})$$

This formula can also be derived from the explicit finite difference method, just in this case the states can be integers between 0 – 255. This operation can actually be considered as an analogy to river lava, where lava fills the trenches represented by objects and spreads out in the image. This is only true if the objects are dark in the

image, if not, the image should be inverted. A grey closure is needed so that the lava cannot drain quickly at the edge of the image. When the operation is completed, this correction image returns the exposure error. Then, in the given step, it is checked whether the value of the current pixel brightness in the modified image is lower than in the original image, if so, I will not change the value of the pixel brightness, if not, the modification will be final. This will result in the image lower brightness intensity areas being replaced by areas with higher brightness intensity. When the required number of steps (approx. A thousand) has elapsed, subtracting the correction image from the original image, then inverting and performing the "autocontrast" operation on it, the error caused by unequal backlighting is no longer visible on the image. The automatic contrast algorithm finds the exact minimum and maximum intensity values in the image and then provides the intensity value of the current pixel for the full range of values.
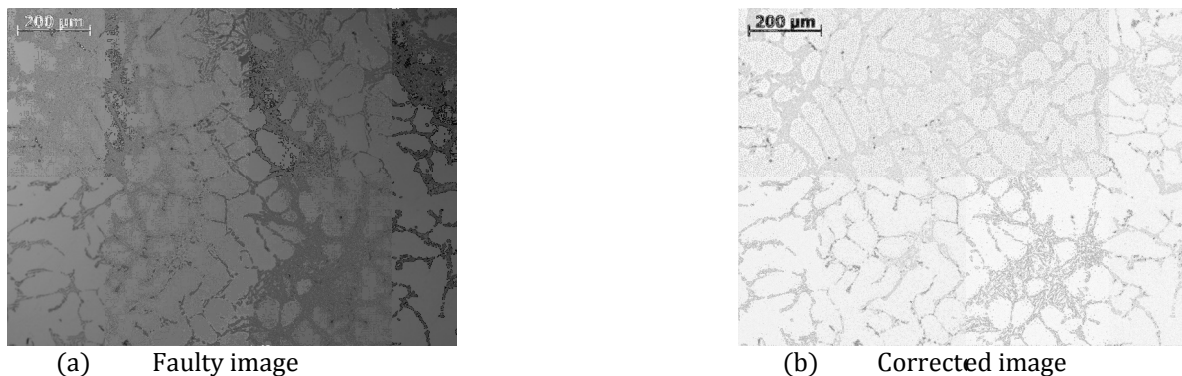

(a)   Faulty image   (b)   Corrected image

Fig. 1. Uneven illumination error and correction.

Arrangement of objects

The data provided by the measuring cellular automata in themselves are not suitable for evaluating the image. To do this data mining is required. The data provided by cellular automata I evaluated using cluster analysis and classification algorithms.

The program for analysing the arrangement of objects is based on the stochastic cellular automata. After the objects are tagged, the boundary conditions are set. In this case, this means that the side pixels on the image are equal to the line one in with the value of the pixels in the column. This is followed by the stochastic cellular automata part of the algorithm. Objects grow until they touch all of their neighbours, but the growth depends on the value of a probability variable P produced by the random number generator. This is necessary because, after a certain step, growing objects take on the shape of the kernel if the growth is deterministic. Each touch event was recorded in a database as follows: the unique identifiers of the matching objects and the number of cellular automata steps. From this database, a dendrogram can then be built, which is suitable for analysing groupings and the arrangement of objects. If touching events run through the image, it results in a morphological mosaic.
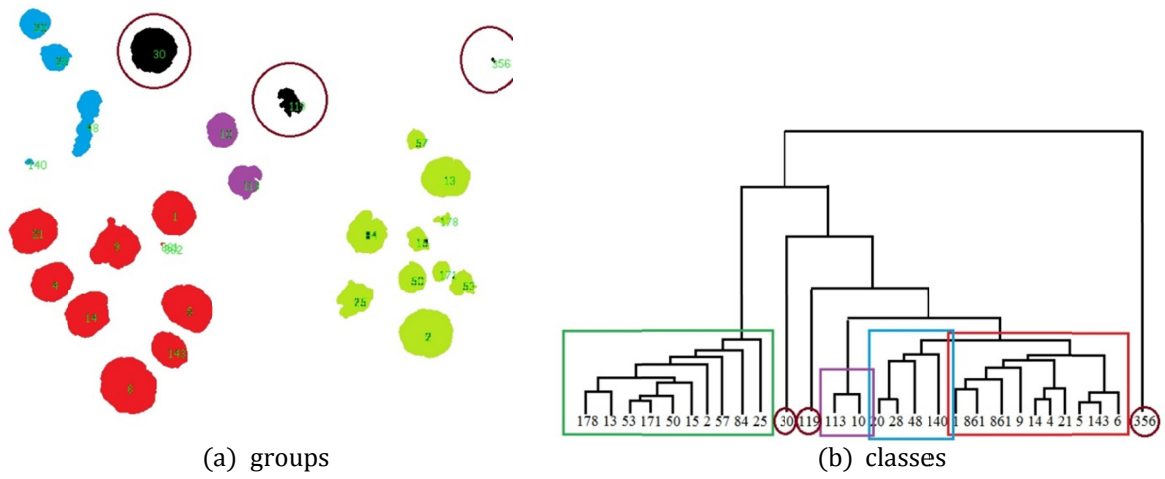
(a) groups   (b) classes

Fig. 2. Groups and classes of spheroidal graphite cast iron objects.
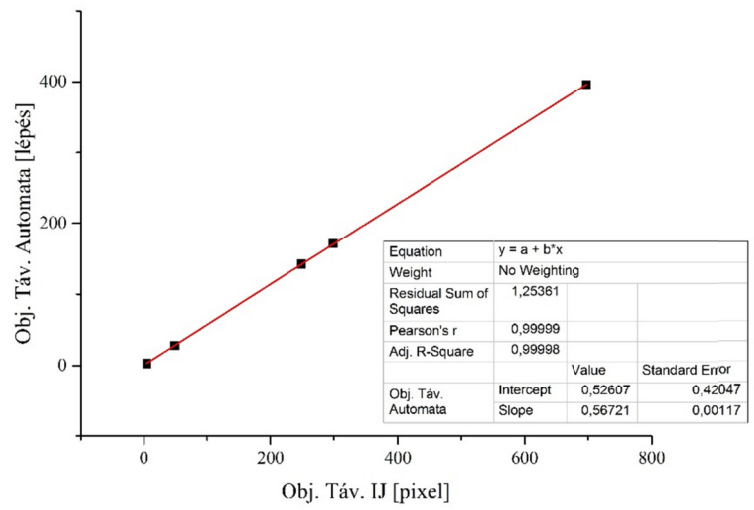
Fig. 3. Calibration diagram of the cellular automaton.

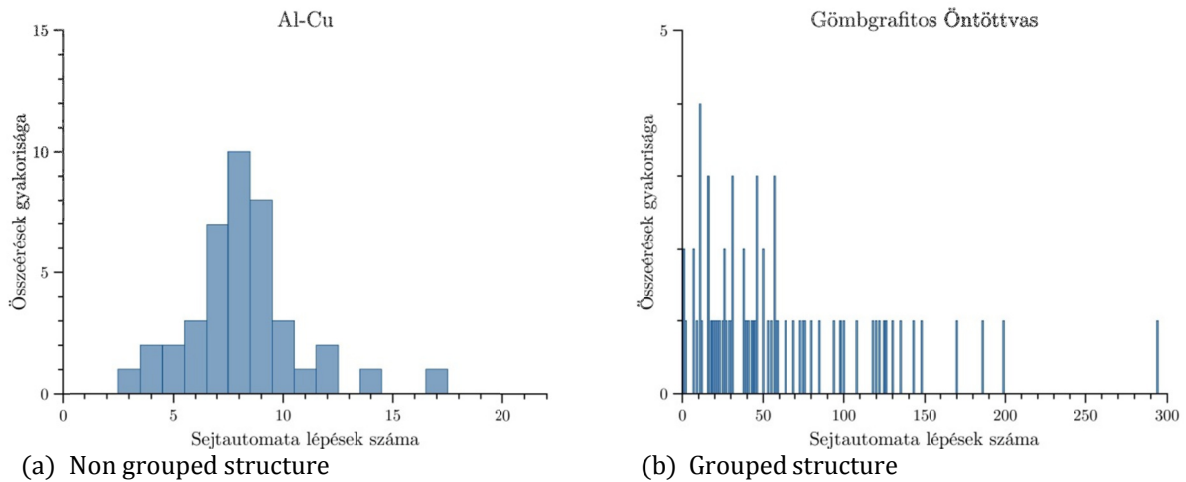(a) Non grouped structure   (b) Grouped structure

Fig. 4. Histogram of object touching events.

Shape recognition of objects

The other cellular automaton produces data suitable for analysing the shape and size of objects. Objects are also tagged with this cellular automaton. In this case, I did not modify the boundary conditions, the universe is also the image. Then, up to a certain number of steps, erosion follows. If all objects disappear, the cellular automaton stops. In each cellular automated step, the unique identifiers of the objects, the number of steps, the perimeter of the object in the given step, and the area of the object in the given step are also registered in a database.
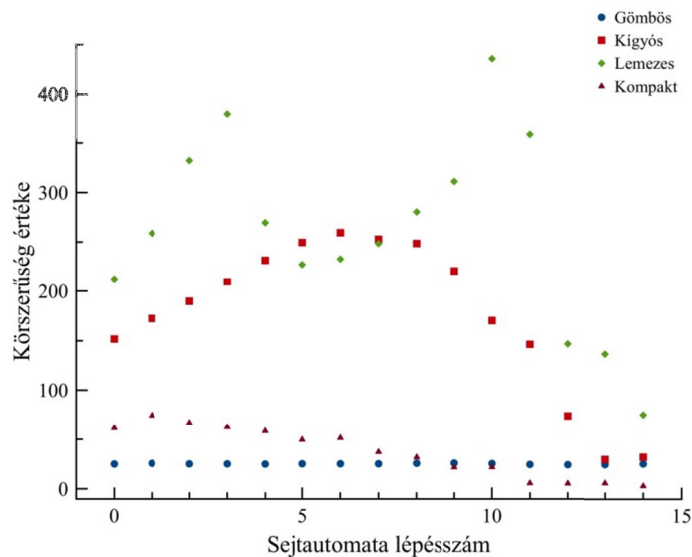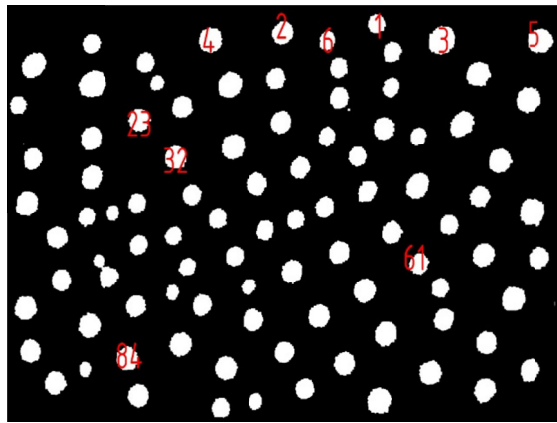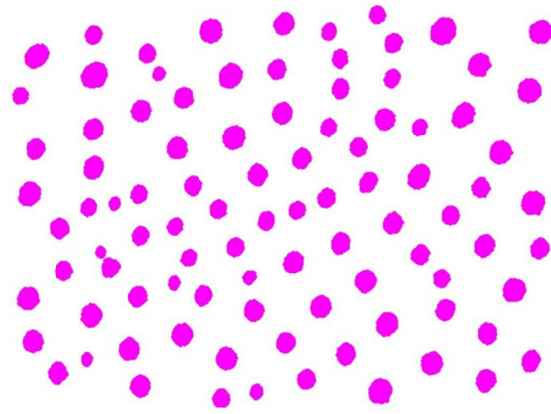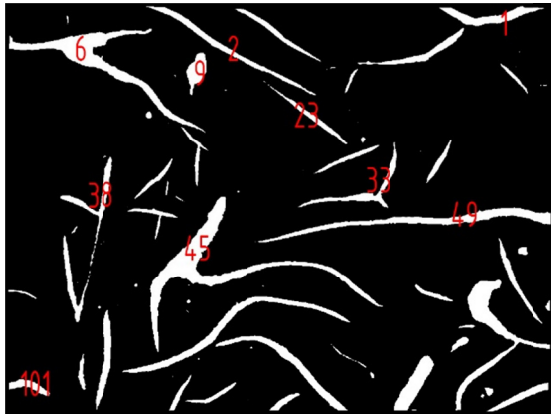

Fig. 5. Dependence of circularity on the cellular number of steps in the case of eutectics of different structures.

(a)　　　SEM image of *Al-Al₃Ni*

(b)　　　Objects of Al–Al3Ni coloured according their shape

(c)　　　SEM image of Lamellar graphite cast iron

(d)　　　Objects of lamellar graphite cast iron coloured according their shape

Fig. 6. Images of different morphologies. Meaning of different colours: red: lamellar, blue: compact, green: "snake like", purple: spheroid

The classification of objects according to shape is carried out by a support vector machine, which was taught using teaching images corresponding to the shapes to be classified.

New scientific results

1. Thesis

During the automatic image analysis of optical microscopic images of eutectic structures, the uneven illumination of the background can be corrected with a so-called *Lava-flow* cellular automaton independently of the illumination error.

a) To do this, we treat the grey image as a terrain, where elevation coordinates are given by intensity values.

b) The "lava" that starts from here constantly fills the holes and ditches in the image.

c) To keep the "lava" within the image, it is necessary to increase the intensity values at the edge of the image by two times, linear closures.

d) As soon as the amount of lava that appears at the point of the eruption overflows the barrier, we get back the background image caused by the illumination error, which can be extracted from the original image to correct the illumination error.
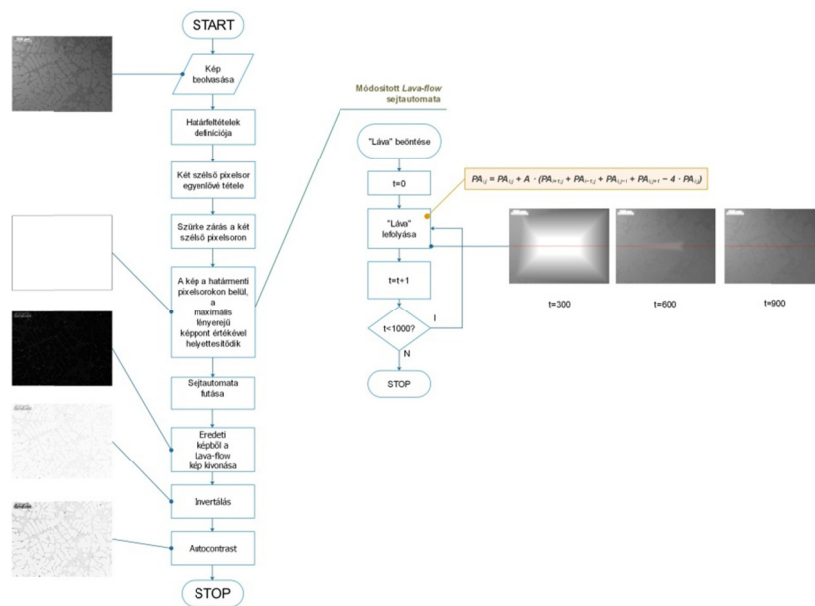

Fig. 7. The flowchart of first thesis.

2. Thesis

During deterministic erosion, the shape and size of the eutectic phases in the image change. Depending on the erosion steps, the change of the shape characteristic formed based on the digital area and perimeter is suitable for shape classification. On microscopic images, the eutectic phases can be classified into four shape types. These are respectively: lamellar, compact, "snake", spherical/rod.

   a) During deterministic erosion, the shape characteristic of each typical shape changes differently. In the parameter space given by the erosion steps and shape characteristic, a eutectic phase appears as a row of dots. Each typical shape has a specific area in this parameter space.
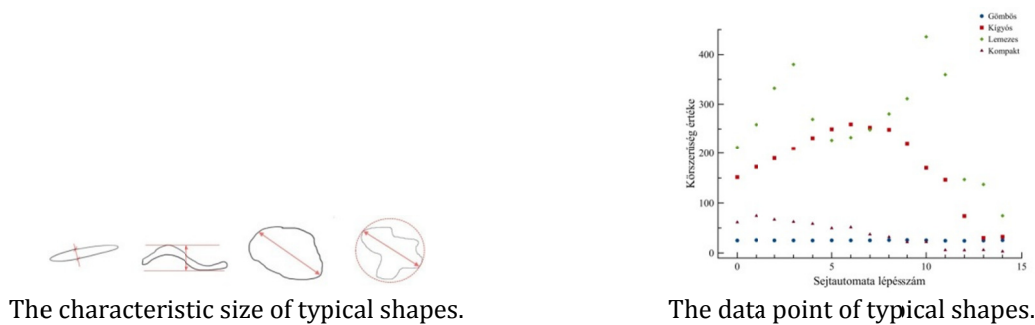

The characteristic size of typical shapes.

The data point of typical shapes.

Fig. 8. The characteristics of identified shapes.

   b) The classification of individual eutectic phases can be done efficiently with a support vector machine.
   c) A eutectic phase is classified in the typical shape class in which the most points characteristic of the phase fall into its validity area.
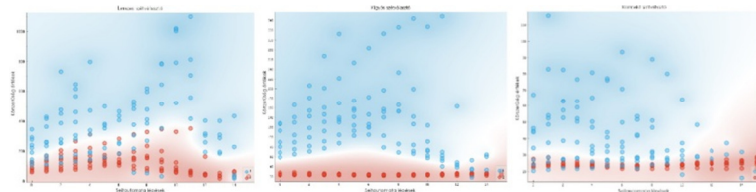

Fig. 9. The steps of classification.

   d) The number of erosion steps associated with its disappearance is proportional to the characteristic linear size of the eutectic phase.
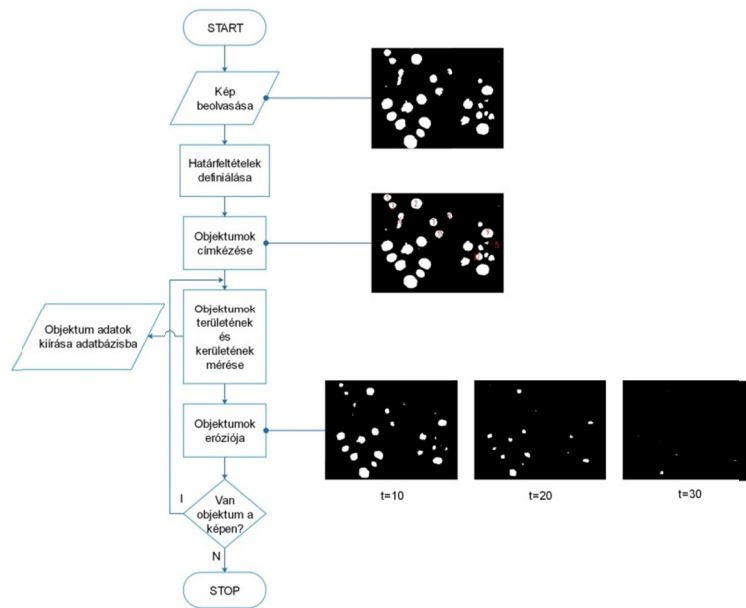   e) The interpretation of the characteristic linear size can be done by knowing the shape.

Fig. 10. The flowchart of second thesis.

3. Thesis

During continuous stochastic dilation, the distance and arrangement of the objects can be determined by registering the first encounters and analysing them. With stochastic dilation, it can be ensured that the contour elements of the eutectic phases move at nearly the same speed.

a) Continuous dilation is applied until the entire image is occupied by the objects.
b) In the meantime, the first encounters are registered as a function of the dilation step.
c) The dilation steps belonging to the first contact are proportional to the shortest distance that can be measured between the contours of the eutectic phases.
d) As the dilation is stochastic, the calibration function needs to be determined for scaling.
e) The calibration function depends only on the random variable of the stochastic dilation.
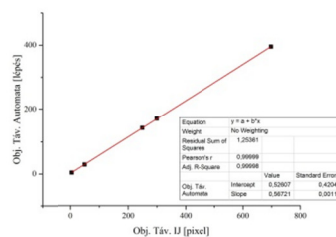

Fig. 11. The calibration diagram, value of the probability variable p=0.5 this value approximates well the slope of the function.

f) In accordance with the combined group analysis, a dendrogram can be drawn up based on the first encounters, on the basis of which the grouping and the analysis of the groups can be carried out.
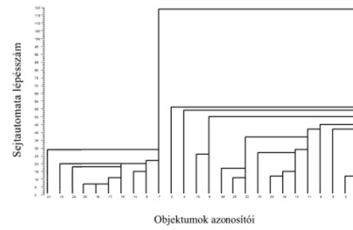
Fig. 12. An example dendrogram.

g) If the eutectic phases do not form groups, then the regularity of their distribution can be checked based on the distribution of the first encounters.
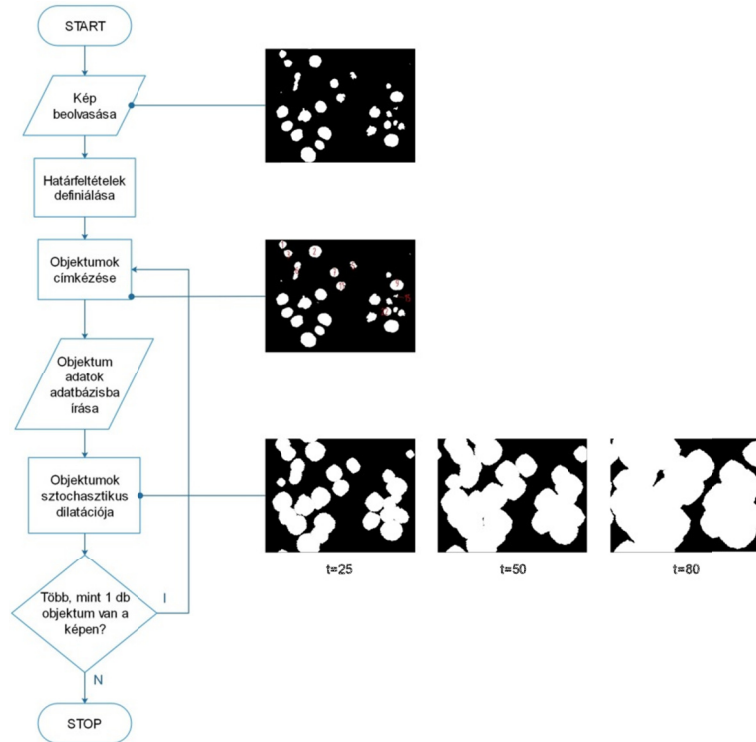

Fig. 13. The flowchart of third thesis.

4. Thesis

The presented automatic image analysis procedure is suitable for processing and evaluating microscopic images of non-eutectic microstructures. The following conditions must be met for this:

a) The procedure distinguishes between two phases: matrix and the phase to be measured.
b) There must be an intensity difference between the phase to be measured and the matrix to such an extent that the *iter* algorithm can segment the phase to be measured. If this condition is not met, choosing another automatic segmentation algorithm can provide a solution.
c) The area ratio of the phase to be measured must be between 10% and 80%. In the case of a value other than this, the *iter* automatic segmentation algorithm does not give an adequate result, a different procedure must be chosen.
d) The minimum linear size of the phase to be measured cannot be less than 10 pixels. In the case of small phases, the shape analysis does not give an appropriate result.

If the listed conditions are met, both the process and results of the analysis and evaluation are evaluated in the same way as in the case of the analysis of microscopic images taken of eutectics.
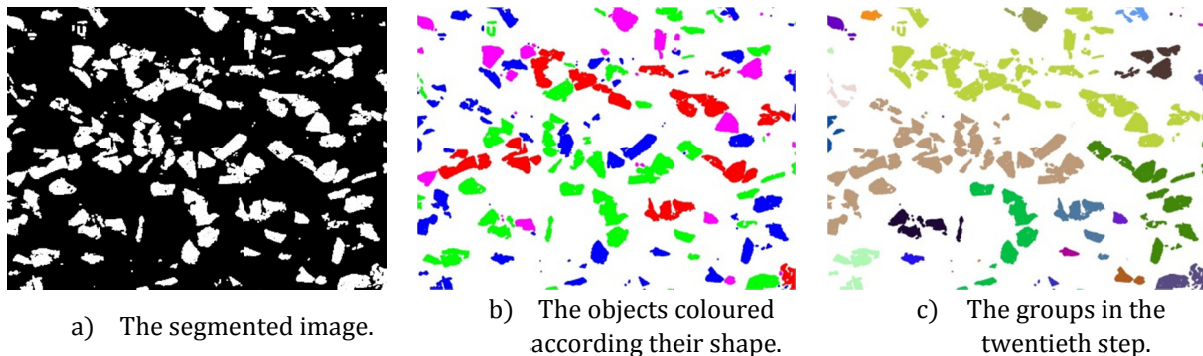

a) The segmented image.   b) The objects coloured according their shape.   c) The groups in the twentieth step.

Fig. 14. The pictures of *Al-SiC20* composite hundred times magnification

Publications

Kornél Bortnyik, Dr. Péter Barkóczy (2016) "Identification of Eutectic Microstructure by HPP Cellular Automata" Materials Science Forum Vol. 885, pp 228-233

Kornél Bortnyik, Dr. Péter Barkóczy (2017) "Examination of Clustering In Eutectic Microstructure" Arch. Metall. Mater. 62, 2B, 1155-1159

Kornél Bortnyik, Dr. Péter Barkóczy, Emese Ivanics, (2016) "Cluster Analysis of Compound Phases in 3003 Al Alloy" The 48th International October Conference on Mining and Metallurgy

Bortnyik Kornél, Léránth Gábor, Dr. Barkóczy Péter (2015) "NYOMÁSOSAN ÖNTÖTT ALUMÍNIUM ALKATRÉSZEK DENDRITES SZERKEZETÉNEK JELLEMZÉSE AUTOMATIKUS KÉPELEMZÉSSEL" X. Országos Anyagtudományi Konferencia

Bortnyik Kornél, Dudás Dóra Daniella (2015) "Irányítottan kristályosított és Mágnesesen kevert Al-Al$_3$Ni eutektikus ötvözet mikroszerkezetének jellemzése számítógépi képelemzéssel" Tavaszi Szél Konferencia 2015

Summary

In addition to today's IT, imaging and manufacturing technology, it has been possible to take microscopic images of a very large number of samples in foundry material testing laboratories. Classical computer image analysis methods require expertise in several disciplines and are not fully automated. Persons performing measurement and / or evaluation need metallographic, materials engineering and in-depth IT skills. There is also the possibility of a human measurement error for manual measurement tasks. So far, only morphology-specific measurement algorithms have existed for eutectic structures with different morphologies. In my thesis I was looking for a solution to automate the process of image analysis, to minimize the need for human intervention, to develop a uniform procedure for every eutectic structure. The first task is to make the images suitable for automatic computer image analysis. The second task is to determine the morphology of the eutectic structure. The third task is to measure the area and perimeter of individual objects, as well as to measure the distance between adjacent objects, and to characterize the arrangement of the objects.

There are also image transformation operations based on cellular automation in classical computer image analysis. Both binary and grey images are suitable for use as a cellular automata universe. A common error in the imaging process of an optical microscope is the unevenness of the backlight. It can be corrected with a *Lava-flow* algorithm-based cellular automaton so that there is no need to use another image. With the help of a deterministic erosion cellular automaton, it is possible to generate a data set, which can then be used to determine the shape of the objects in the image using time series analysis. With the help of a stochastic dilatation cellular automaton, a data set can be extracted from the image, which can be used for hierarchical cluster analysis. From this, the arrangement of the objects can be determined. The distance between adjacent objects can also be extracted from the data of the cellular automaton. These algorithms can be used in both optical and scanning electron microscopy images. The minimum object size required for the method to be applicable is such that the object disappears from the image only after five erosion steps. In the case of smaller objects, its shape can only be determined with great uncertainty. This limitation is also true for classical image analysis methods due to the pixel nature of the image. The methods were validated on SEM images, lamellar $Al - Cu$, spherical $Al - Ni$ images. Optical microscopic images were used for spherical, compact, "snake-like", lamellar cast irons and refined and unrefined $Al - Si$ eutectics. The shape recognition algorithm was applied to each structure and the manual area and perimeter were checked. The result of the shape recognition was checked visually. Using a cellular automation algorithm based on stochastic dilatation, the distance between adjacent objects was measured. Using the data, a hierarchical cluster analysis was carried out. With the help of the methods presented here, the personnel performing image analysis need less IT expertise, and human intervention can be minimized. This speeds up the image analysis process, making it possible to analyse a large number of samples as the measurement accuracy increases. Furthermore, automation allows the image analysis system to be integrated into industry 4.0 technologies. Taken together, this can enable a plant to produce cost-effectively, efficiently and with high quality.