Automatic texture classification of metallographic images by Gabor Filter

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ABSTRACT
In this paper an alternative method for the automatic pattern classification of metallographic images is presented. The aim of the pattern classification is to help monitoring the process quality in the steel plant of the company ArcellorMittal Ostrava plc, Ostrava, the Czech Republic. The here presented approach is based on the well known Gabor filter, which provides suitable results in various texture analysis applications. In our case, the real metallographic samples are firstly separated from the image background. Then, a texture extraction is provided. The extracted samples are processed by applying the Gabor filter with various properties, from which selected texture features are formed. Effects of a dimension reduction technique for quality of similarity retrieval are studied.

Keywords
metallography, LSI, Gabor wavelet, texture analysis, industrial applications, image retrieval

1. INTRODUCTION
The aim of our research activity is to develop and test methods for visual analysis of digital images of metallographic samples. For quality modeling of metallographic images, it is important to retrieve visually similar images according to a user defined image, a query image.

The steel plant produces variety of steels with various properties, according to needs of consumers (pipes, building structures, energetics - metals for transformers, etc.). Steel samples from the cast billets are taken from continuous casting machine. These are crosscuts of the cast billets. These samples are conveyed into the metallography laboratory where they are mechanically adjusted. In order to stress a sample macrostructure, crosscut etching is done [Zeljkovic09].

Consequently, digital photographs of these etched crosscuts are being taken. In our digital image database, we try to recognize two basic production technologies of steels: alloyed and carbonic, see their different textures (Figure 2). The alloyed structure of image samples is characterized by visible segments. On the other hand, carbonic samples have small-grained structure without grains. Moreover, there are two basic shapes of metal samples, square and round.

Metallographic laboratories of ArcelorMittal Ostrava a.s. uses a system of standards for marking the macro structures. Usually this classification is not easy. For this reason, we represent digital images by feature vectors, which represent information hidden in textures of digital images of metallographic samples. Recently, we experimented with feature vectors obtained by the wavelet transformation and the eigen-space analysis. In all cases, the feature vector can be viewed as a sequence of image descriptors [Praks08a, Praks08b]. In this paper, an industrial application of the texture retrieval by the Gabor filter is presented.

The paper is structured as follows. Section 2 describes the theoretical background of the Gabor filter for the texture analysis. In Section 3, three used image similarity models are presented. The experimental comparison of these approaches for the image classification follows in Section 4, while Section 5 closes the paper with conclusions and future works.

2. GABOR FILTER

In this section we describe fundamentals of 2D Gabor filters for the texture analysis. We show how texture samples could be represented in order to reduce the amount of data generated for the comparison. We refer to [Kruz00a], [Zhan00a] and [Man00a] for the general description of Gabor wavelets and further details in this topic. Also we refer readers interested in wavelets to [Fraz00a].

Gabor wavelet

For an image *I(x,y)* with size *PxQ* is the Gabor wavelet transform defined as

$$\hat{I}=\iint_{S,T} I(x-s,x-t)*\bar{\Psi}_{mn}(s,t)\,ds\,dt, \quad (1)$$

where *S* and *T* correspond to the wavelet size. Moreover, $\bar{\Psi}_{mn}(x,y)$ is the complex conjugate of $\Psi_{mn}(x,y)$, which is the self-similar Gabor wavelet. Finally, $\Psi_{mn}(x,y)$ is generated from the mother-wavelet

$$\Psi(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}e^{\frac{-1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)}\cos(2\pi x\lambda), \quad (2)$$

where σ_x and σ_y are standard deviations of the gaussian envelope and λ is the wavelength of the cosine factor.

In the next text *m* and *n* will range from 1 to *M* and from 1 to *N*, respectively.

The self-similar Gabor wavelet is defined through multiples of mother-wavelet:

$$\Psi_{mn}(x,y)=a^{-m}\Psi(\tilde{x},\tilde{y}) \quad (3)$$

with *m* and *n* specifying scale and orientation of the function respectively, and

$$\begin{aligned}\tilde{x}&=a^{-m}(x\cos(\phi)+y\sin(\phi))\\ \tilde{y}&=a^{-m}(-x\sin(\phi)+y\cos(\phi))\end{aligned}, \quad (4)$$

where $a>0$ and $\phi=n\pi/N$.

All variables above are adopted from [Zhan00a] and are defined as follows:

$$a=\left(\frac{U_h}{U_l}\right)^{\frac{1}{M-1}}, \quad (5)$$

$$\lambda_{m,n}=a^m U_l, \quad (6)$$

$$\sigma_{x,m,n}=\frac{(a+1)\sqrt{2\ln(2)}}{2\pi a^m(a-1)U_l}, \quad (7)$$

$$\sigma_{y,m,n}=\frac{1}{2\pi\tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U_h^2}{2\ln(2)}-\left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}}. \quad (8)$$

We chose $U_h=0{,}4$ and $U_l=0{,}05$, because these values are widely used in the literature.

On Figure 2 a sample filter bank, we used in our experiments, with four angles and five frequency scales is shown.

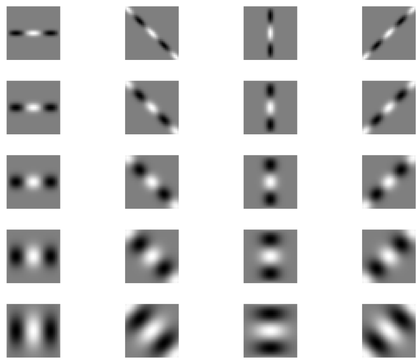

Figure 1: Sample Gabor filter bank for M=5 and N=4.

Texture sample representation

Here we show how to use the frequency information obtained via Gabor wavelets to form features that fully represents the given texture sample.

$$\mu_{mn}=\iint_{xy}|\hat{I}(x,y)|\,dx\,dy \quad (9)$$

$$\sigma_{mn}=\iint_{xy}\sqrt{\left(|\hat{I}(x,y)|-\mu_{mn}\right)^2}\,dx\,dy \quad (10)$$

where symbols μ_{mn} and σ_{mn} denotes mean and standard deviation of frequency responses to Gabor filters, respectively.

For the further refinement of the given metallographic samples we used a circular ratio, as we have to split square samples and circular ones. The circular ratio is defined as

$$C = \frac{A_R}{A_B} \, , \tag{11}$$

where A_R is area of the whole (segmented) sample and A_B is area within the bounding box, respectively. The value of *C* will be close to 1 for rectangular shapes and less than 1 for any other shapes. Since we have only rectangular and circular samples, we use only one feature for the shape description of the analyzed sample.

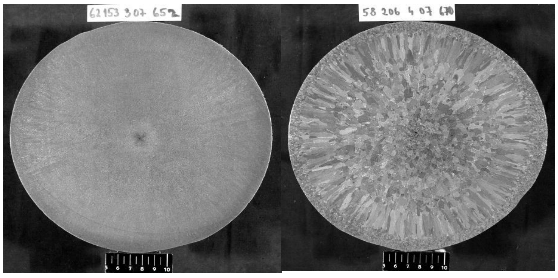

Figure 2: Example of two different textures of metallographic samples: carbonic (left) and alloyed (right).

3. SIMILARITY MEASURING

The goal of the similarity measurement is to find similar samples, which are described by the feature vector defined in Section 2.

For similarity measurement three types of measure were studied. We used a standard cosine similarity defined as

$$\varphi = \frac{x \cdot y}{\|x\| \|y\|} \, , \tag{12}$$

which describes an angle between vectors *x* and *y.* A small angle mean vectors are close ("similar") to each other.

The distance between two responses to Gabor filter is defined as

$$d_{mn}(i\,,\,j) = \sqrt{(\mu_{mn}^{i} - \mu_{mn}^{j})^2 + (\sigma_{mn}^{i} - \sigma_{mn}^{j})^2} \, . \tag{13}$$

The distance between two feature vectors is defined as a sum of all responses to the Gabor filter,

$$D(i\,,\,j) = \sum_{m} \sum_{n} d_{mn}(i\,,\,j) \, . \tag{14}$$

We also studied an effect of the dimension reduction on accuracy of the measurement.

For this task the Singular value decomposition (SVD) was used. SVD is defined as

$$A = U \, \Sigma \, V^T \tag{15}$$

where *A* is a document matrix, *U* and *V* are matrices having reduced document and keyword dimension respectively and Σ is a diagonal matrix with singular values. This kind of dimension reduction is also used for the latent semantic indexing (LSI). Details of LSI and SVD could be found in [Lars00a].

A dimension reduction has several positive affects on the original document matrix. It reduces amount of information needed for image descriptors. Moreover, it is used for automated noise reduction [Praks08b].

4. RESULTS

For our experiments we build two training databases both having unique texture samples that represents typical members of all metallographic images in our data set. These two databases have 3 and 5 distinct textures for each type of data.

For experiments we compared results of all three similarity measurement methods described in the previous section.

The query database was constructed from 42 different samples. Some samples were chosen to be the same as in the training database for verification.

Results for both training databases are shown in Table 1. For example, when the cosine similarity is used, there was only one image retrieval failure in 42 retrieved cases, which gives us the probability of incorrect retrieval 1/42 ~ 2.4 %. Some visual results are presented in Figure 3 and Table 2. In order to achieve well arranged results, only the most significant images are presented. Image retrieval results are presented by decreasing order of similarity. The query image is situated in the upper left corner. The similarity of the query image and the retrieved image is also presented. In order to achieve well arranged results, only 7 most visually similar images are presented.

training set	lsi	cosine	tex. dist.
3	28,5%	2,4%	31%
5	12%	2,4%	35,7%

Table 1: Results for similarity measure – probability of incorrect retrieval.

Our experiments show that all three methods prove to be successful in detecting similar samples, but each of them has advantages and disadvantages.

The cosine similarity is the most accurate and robust to training set size, but is sensitive to noise in the texture data.

The texture distance is relatively stable towards the size of the training data and seems to be less sensitive to noise.

LSI shows to have worse results for training set of size 3 and better size 5. This is not unexpected result. LSI in its nature reduces the number of required data needed for the object representation. This principle works well for large sets of data, but it is irrelevant for small data sets. This will result in removing information needed for the successful classification of the texture sample. For small data-sets, it is very difficult to distinguish the signal-to-noise ratio.

Image	Similarity
SCK60U9.jpg	1
SCK60U14.jpg	1
SCK60U36.jpg	1
SDK53M29.jpg	0.9998

Table 2: An example of image retrieval results by the Gabor filter without LSI.

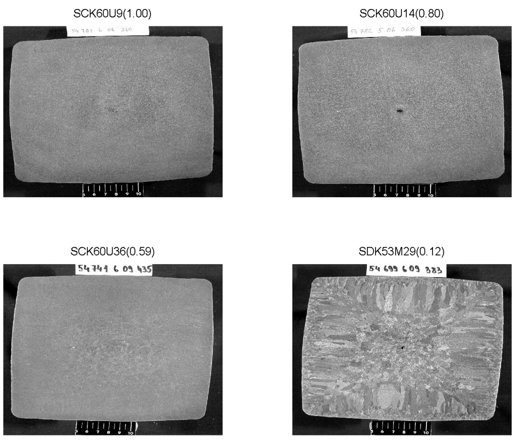

Figure 3: An example of LSI image retrieval results by the Gabor filter.

5. Conclusions

The objective of this research is visual monitoring of properties of various steels in the steel plant. The experimental digital images of metallography samples have been provided by the company ArcelorMittal Ostrava plc (Ostrava, Czech Republic).

In this paper, we presented an industrial application of the Gabor filter for texture retrieval of metallographic macro-structures. It is a combination of the Gabor filter representation with image retrieval by LSI, which was applied in a real industrial environment. The first results prove high performance of the image retrieval results. Our results indicate that the Gabor filter method can automatically recognize the shape (square vs. round) and the type of images found in our image database (alloyed vs. carbonic samples). The shapes of samples were recognized in all case without any problems. For the texture retrieval, the probability of the recognition error for alloyed vs. carbonic samples is only 2,4% for the cosine similarity measure. The here presented image retrieval results are very consistent with the human expert opinion [Praks08a]. In the future, it would be interesting to detect, extract and analyze detailed metallurgical relations in images, which are hidden in the digital image database of metallographic samples.

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