Material Classification Using Morphological Pattern Spectrum for Extracting Textural Features from Material Micrographs

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Abstract. In this paper, we address one very important industrial application of computer vision – automatic classification of materials. In our work, we have considered materials that are mixtures of two or more elements. Such materials are called alloys. It is observed at the microscopic level that an alloy is composed of small randomly distributed crystals of varying shapes and sizes called grains. Also, the color and hence the intensity of the grains vary in alloys. Generally, this shape-size-intensity distribution of the grains is different for different materials. This means micrographs obtained from different materials form texture-like images that differ from one material to another in appearance. Therefore, in principle, any texture analysis method may be used for material classification. In our method, we propose to extract textural features corresponding to grain geometry and intensity and use them for analysis and classification of alloys. These features are extracted via gray-scale morphological operations and are measured in terms of Size-Intensity-Diagram (SID) and Tri-variate Pattern Spectrum (TPS) coefficients. In our experiments, we achieved 83.43% and 89.43% classification accuracies in cases of SID and TPS, respectively. This demonstrates the effectiveness of the proposed method for material classification which in turn confirms that our choice of features is indeed appropriate for the purpose.

1 Introduction

In recent years, Computer Vision has been extensively used in real world systems for commercial, industry and military applications. Some of these applications include industrial automation, biometrics, 3D modelling, video surveillance, classification and recognition, document analysis, medical analysis, human-computer interaction, robotics and so on. In the field of industrial automation, its applications include nondestructive quality and integrity inspection, on-line measurements, etc. thereby aiding the process of manufacturing and inspection. Consequently, computer vision related technologies have started migrating from academic institutions to industrial laboratories.

The objective of this paper is automatic classification of materials which may find application in industry and material science research. However, in this paper,

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we do not intend to develop any new algorithm for material classification but to build up a system that will view a material sample at microscopic level and will subsequently classify it on the basis of some visual features extracted from the micrograph making use of some existing image processing and computer vision techniques.

In our present work, we have considered materials that are mixtures of two or more elements. Such materials are called *alloys*. Different elements mixed in different proportions give different types of alloys. It is observed at the microscopic level that an alloy is composed of small randomly distributed crystals of varying shapes, sizes and colors called grains. This means a material micrograph obtained from an alloy resembles a texture image in which the grains form the texels (texture elements). It is also observed that the shape-size-color distribution of the grains generally differs from one material to another. As a consequence, texture images obtained from the micrographs of different types of materials generally look different in appearance. Therefore, in principle, any texture analysis method may be used for material classification. Based on this principle, some texture-based material classification schemes had been proposed in [1], [2], [3], [4] and [5]. However, these methods do not take into account the grain geometry and color which otherwise seem to be the most appropriate characterizing features in the context of material classification. On the other hand, the structure of the texture primitive elements (texels) is one very useful and important feature that may be used for the purpose of texture analysis and classification. Therefore, it makes sense to classify materials by extracting textural features corresponding to grain shape and size from the texture-like material micrographs and then apply any available texture classification scheme.

It has been demonstrated through research in material science that the shape and size of the grains composing a material provide important information necessary for characterizing the material, as mentioned in [6] and [7]. In view of this, an earlier attempt to classify materials on the basis of grain size was proposed in [8]. The method involves grain boundary detection and moment calculation. Another efficient tool for shape-size analysis used frequently in image processing and computer vision applications is the mathematical morphology [9]. This is mainly due to its capability in extracting grain geometry and structural information efficiently. Accordingly, some morphological approaches for shape-size based texture analysis were developed in [10], [11], [12] and [13]. Consequently, any of these texture analysis methods may be used for material classification. One such method for material grain size determination using morphological texture analysis is given in [14]. But, all these methods are based on shape-size analysis only and hence are suitable only in cases where color information does not play any significant role.

Apart from grain geometry, another important property that distinguishes one material from another in appearance is the color. An impure material, for example an alloy, when viewed at the microscopic level will show variation in grain color depending on the concentration and nature of different types of crystals composing the material. As a result, a brilliantly white pure material may become cream, grey, pink, brown, or even red due to impurities contained in the crystal structure even in trace amounts. Therefore, extraction of grain color information, in addition to grain shape and size, is equally important for achieving better accuracy in material classification. However, in order to reduce computational complexity, in our work we use monochrome images only where grain color variation manifests as intensity variation in the micrographs. Accordingly, in our work we use gray-scale morphology which is capable of deriving information regarding intensity variation, in addition to shape and size.

2 Proposed Method

Mathematical morphology is an useful tool in many image processing applications that involve shape analysis. In particular, the Pattern Spectrum proposed by Maragos [15] gives us the size distribution of objects within a given image. Extension of the Pattern Spectrum to gray images is the Size Intensity Diagram (SID) [16] which gives a breakdown of the size and gray-level distribution of objects in an image. Another variant of the basic Pattern Spectrum is the Bivariate Pattern Spectrum (BPS) [17] which yields the shape-size distribution in true sense, while the Tri-variate Pattern Spectrum (TPS) [18] is the extension of BPS to gray images. TPS generates the size, gray-level and shape distribution under a single framework. In this paper, we now propose to build up a material classification system based on texture analysis using two variants of the basic Pattern Spectrum, viz., Size-Intensity Diagram and Tri-variate Pattern Spectrum, that give information about the shape, size and intensity variation in a gray image.

2.1 Basic Morphological Operations on Binary Images

The two basic operations in morphology are *dilation* and *erosion*. Given a 2-dimensional image, the object(s) present in it may be represented as a set $\mathbf{A}$ whose elements are the coordinates of the object pixels. Therefore, $\mathbf{A}$ is a set in a 2D Euclidean space $\Re^2$, i.e., $\mathbf{A}=\{(a_x, a_y)\}$ where (a_x, a_y) are the coordinates of the object pixels. Let, $\mathbf{B}$ be another set in $\Re^2$ given as $\mathbf{B}=\{(b_x, b_y)\}$. Then dilation and erosion of $\mathbf{A}$ w.r.t. $\mathbf{B}$ are defined as

$$\textit{Dilation:} \quad \mathbf{A} \oplus \mathbf{B} = \bigcup_{(b_x,b_y)\in\mathbf{B}} \left\{(a_x, a_y) + (b_x, b_y) \;\middle|\; (a_x, a_y) \in \mathbf{A}\right\} , \tag{1}$$

$$\textit{Erosion:} \quad \mathbf{A} \ominus \mathbf{B} = \bigcap_{(b_x,b_y)\in\mathbf{B}} \left\{(a_x, a_y) - (b_x, b_y) \;\middle|\; (a_x, a_y) \in \mathbf{A}\right\} . \tag{2}$$

The set $\mathbf{B}$ is called the structuring element (SE). Combinations of dilation and erosion give two other morphological operations as follows:

Opening: $$O(\mathbf{A},\,\mathbf{B}) = \mathbf{A} \circ \mathbf{B} = (\mathbf{A} \ominus \mathbf{B}) \oplus \mathbf{B}\ , \tag{3}$$

Closing: $$C(\mathbf{A},\,\mathbf{B}) = \mathbf{A} \bullet \mathbf{B} = (\mathbf{A} \oplus \mathbf{B}) \ominus \mathbf{B}\ . \tag{4}$$

The opening operation acts as a morphological filter in the sense that it retains only those object(s) where the SE can fit in and eliminates the remaining object(s). Closing operation is essentially the opening of the complemented input.

2.2 Pattern Spectrum

A quantitative measure for the size distribution of the objects in an image is the Pattern Spectrum. The number of pixels in the set obtained by subtracting the opened objects from the original one gives the area of those objects that cannot contain the SE. Thus, iterative application of the morphological opening and the measurement of the residues, while increasing the size of the SE, gives the size distribution of the objects contained in the given image. So, if $\mathbf{A}$ is the set representing the objects in a given 2D image, then following [9] and [19] the pattern spectrum or *pecstrum* may be defined as

$$PS_{n\mathbf{B}}(\mathbf{A}) = \frac{1}{Mes(\mathbf{A})}\Big[Mes(\mathbf{A} \circ n\mathbf{B}) - Mes(\mathbf{A} \circ (n+1)\mathbf{B})\Big]\ , \tag{5}$$

where $Mes(\cdot)$ denotes the finite set cardinality and $n\mathbf{B}$ is the expanded SE of size n (n is any integer in the range 0 to $+\infty$) obtained by dilating $\mathbf{B}$ iteratively for $(n-1)$ times, i.e.,

$$n\mathbf{B} = \mathbf{B}\underbrace{\oplus \mathbf{B} \oplus \ldots \oplus \mathbf{B}}_{n-1 \quad times}\ . \tag{6}$$

2.3 Bivariate Pattern Spectrum

The pattern spectrum defined above, does not convey the information about the shapes of the objects present in the image. This drawback may be overcome by using Bivariate Pattern Spectrum (BPS). Unlike the usual Pattern Spectrum described above, the size of the SE is increased in vertical and/or horizontal direction so as to vary both the size and the shape of the SE. Thus, the residues so obtained at all stages of opening and subsequent subtraction give the shape distribution of the objects to some extent, in addition to the size description. Therefore, BPS is the generalization of the usual Pattern Spectrum and is the true shape-size descriptor for the objects present in the given binary image. Accordingly, the BPS is defined as

$$\begin{aligned} &BPS_{((n_x,n_y)\mathbf{B})}(\mathbf{A}) \\ &\quad = \tfrac{1}{Mes(\mathbf{A})}\{Mes(\mathbf{A} \circ (n_x,n_y)\mathbf{B}) + Mes(\mathbf{A} \circ (n_x+1,n_y+1)\mathbf{B}) \\ &\qquad -Mes(\mathbf{A} \circ (n_x+1,n_y)\mathbf{B}) - Mes(\mathbf{A} \circ (n_x,n_y+1)\mathbf{B})\}\ , \end{aligned} \tag{7}$$

where $(n_x,n_y)\mathbf{B}$ is the SE of dimension n_x by n_y.

2.4 Basic Morphological Operations on Gray Images

A gray scale image is defined as a 2D function $f(a_x, a_y)$ where (a_x, a_y) is the coordinate of a pixel in the image and $f(a_x, a_y)$ gives the corresponding pixel intensity. The object present in the image, hence, may be defined in the form of a set of triples $\mathbf{A} = \{(a_x, a_y, a_g)\}$ where (a_x, a_y) are the object pixels and $a_g = f(a_x, a_y)$. The gray scale structuring element $\mathbf{B}$ may also be defined in a similar way in the form of a set $\{(b_x, b_y, b_g)\}$. The morphological operations on the image $\mathbf{A}$, hence, are defined in [19] and [20] as

Gray scale dilation:

$$\mathbf{A} \oplus \mathbf{B} = \underset{(b_x,b_y,b_g)\in\mathbf{B}}{\text{EXTSUP}} \left| \{(a_x, a_y, a_g) + (b_x, b_y, b_g) \,\middle|\, (a_x, a_y, a_g) \in \mathbf{A}\right\} \ , \tag{8}$$

Gray scale erosion:

$$\mathbf{A} \ominus \mathbf{B} = \underset{(b_x,b_y,b_g)\in\mathbf{B}}{\text{INF}} \left| \{(a_x, a_y, a_g) - (b_x, b_y, b_g) \,\middle|\, (a_x, a_y, a_g) \in \mathbf{A}\right\} \ . \tag{9}$$

The opening and closing operations are defined as their counter parts in binary operations.

2.5 Size Intensity Distribution

Using the idea of the Pattern Spectrum, and incorporating gray level (intensity) information, Size-Intensity Diagram (SID) is obtained as

$$\begin{aligned} SID_{((n,g)\mathbf{B})}(\mathbf{A}) = \frac{1}{Mes(\mathbf{A})} \{&Mes(\mathbf{A} \circ (n,g)\mathbf{B}) + Mes(\mathbf{A} \circ (n+1, g+1)\mathbf{B}) \\ &-Mes(\mathbf{A} \circ (n+1, g)\mathbf{B}) - Mes(\mathbf{A} \circ (n, g+1)\mathbf{B})\} \ , \end{aligned} \tag{10}$$

where $(n, g)\mathbf{B}$ is a flat SE of size n with gray level g.

2.6 Tri-variate Pattern Spectrum

Using the above relations for the gray scale morphological operations, the idea of BPS is extended to Tri-variate Pattern Spectrum (TPS) so as to obtain the shape-size description in a gray scale image. In the TPS, the shape of the structuring element $\mathbf{B}$ is varied via separate expansion in the x and y dimensions together with the variation of gray levels of the structuring element. The TPS defined at each gray level g is defined as

$$\begin{aligned} &TPS_{((n_x,n_y,g)\mathbf{B})}(\mathbf{A}) \\ &= \tfrac{1}{Mes(\mathbf{A})} \{Mes(\mathbf{A} \circ (n_x, n_y, g)\mathbf{B}) + Mes(\mathbf{A} \circ (n_x+1, n_y+1, g)\mathbf{B}) \\ &\quad -Mes(\mathbf{A} \circ (n_x+1, n_y, g)\mathbf{B}) - Mes(\mathbf{A} \circ (n_x, n_y+1, g)\mathbf{B})\} \ , \end{aligned} \tag{11}$$

where $(n_x, n_y, g)\mathbf{B}$ is a flat structuring element of dimension n_x by n_y with gray level g, $g = 1, 2, \ldots, L-1$, L is the number of gray-levels in the image. Gray level $g = 0$ generally corresponds to the inter-grain gaps and cavities and hence is not considered in evaluating the TPS coefficients.

2.7 Material Classification Using SID and TPS

Using Scanning Electron Microscope, microscopic images of materials known as micrographs are obtained. These micrographs are subsequently converted to gray images. As mentioned before, at the microscopic level, it is observed that materials are made up of grain patterns that give texture-like appearance to the micrographs. Also, the shape, size and intensity distribution of grains in one material is generally different from that of another material. This aspect of the micrographs is utilized for the purpose of material classification. In other words, a material may be recognized on the basis of the shape, size and intensity distribution of the grains that the material is composed of. And for the purpose of feature extraction from different materials the SID and TPS seem to be suitable in the present context while classification may be accomplished by employing any gray texture analysis scheme.

As with binary textures, gray-scale morphological approach seems to be an efficient tool in gray texture analysis involving grain shape analysis. One such morphological approach to gray texture analysis is given in [21] in which a model of the elementary particles that form a texture is obtained by applying pattern spectrum with gray-scale structuring elements. However, in this method, the extra step necessary to determine optimal structuring elements increases the computational overhead. In later times, a TPS-based texture analysis scheme had been developed in [22] which may be applied on material micrographs so as to accomplish material classification. However, TPS is generally computationally expensive. A relatively less complex scheme may be to use SID in place of TPS but at the cost of classification accuracy. The set of SID or TPS coefficients forms the set of textural features corresponding to shape, size and intensity of the material grains and is subsequently used in the classification stage.

3 Experimental Results

In our experiments, we have evaluated the accuracy in classifying different materials by applying texture analysis on material micrographs in which the textural features are measured in terms of SID and TPS coefficients, as proposed in this paper. Seven different types of materials with 250 training and 50 test micrographs per material type are taken. The colored micrographs are converted to gray images with 256 gray levels. The basic structuring element taken is a 3×3 square and a k-NN classifier is used for classification. The different types of materials taken are (A) Copper-Zinc alloy, (B) Steel with 0.1% Carbon, (C) Steel with 0.5% Carbon, (D) Silicon-Carbide (E) Steel with 0.4% Carbon, (F) Steel with 1.25% Carbon, and (G) Ferrite XIV. Figure 1 shows the micrographs for each of these materials, one sample per material type. The classification results obtained in our experiments are given in Table 1 and Table 2.

We see that the proposed material classification scheme using SID and TPS coefficients works well yielding accuracy rate as high as 100% for some materials while the overall recognition rates are 83.43% and 89.43% in cases of SID and TPS, respectively. From Fig. 1, we see that the microscopic views of some materials are so similar (e.g., CuZn and Steel with 0.1% Carbon) that manual discrimination is almost impossible. Even then, our classifier is capable of discriminating them to some extent. We also observe that TPS yields better recognition rate compared to SID, but at the cost of increased computational load. This is because TPS has better shape analyzing capacity than SID.

Table 1. Recognition result in material classification using SID coefficients. Seven different types of materials are taken and our proposed classification method is tested on 50 samples per material type.

Class labels of input test samples	Number of test samples classified to to each of the seven material classes							Recognition Rate in percentage
	A	**B**	**C**	**D**	**E**	**F**	**G**	
A	31	15	0	2	1	1	0	62.0
B	1	45	2	1	0	1	0	90.0
C	1	1	36	6	0	6	0	72.0
D	0	0	0	50	0	0	0	100.0
E	0	0	0	0	50	0	0	100.0
F	0	0	0	4	16	30	0	60.0
G	0	0	0	0	0	0	50	100.0
	Average Recognition Rate							83.43

Table 2. Recognition result in material classification using TPS coefficients. Seven different types of materials are taken and our proposed classification method is tested on 50 samples per material type.

Class labels of input test samples	Number of test samples classified to to each of the seven material classes							Recognition Rate in percentage
	A	**B**	**C**	**D**	**E**	**F**	**G**	
A	35	8	1	2	0	4	0	70.0
B	0	40	1	1	1	7	0	80.0
C	0	0	44	0	0	6	0	88.0
D	0	0	0	50	0	0	0	100.0
E	0	0	0	0	50	0	0	100.0
F	0	0	0	5	0	45	0	90.0
G	0	0	0	0	0	1	49	98.0
	Average Recognition Rate							89.43

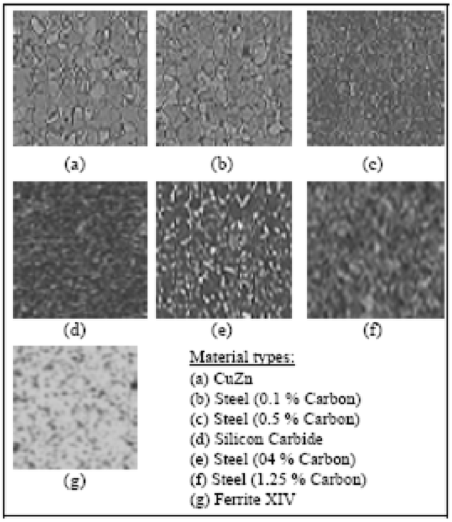

Fig. 1. Micrographs of the seven different types of materials used in our experiment. For computational simplicity the actual color micrographs have been converted to gray images as shown here. The texture like appearance of the micrographs can be observed in the figures.

4 Conclusion

In this paper, we have explored the potentiality of using morphological pattern spectrum for material classification. Two variants of the morphological Pattern Spectrum, namely the Size-Intensity-Diagram (SID) and the Tri-variate Pattern Spectrum (TPS), are used for extracting textural features from the texture-like microscopic images of the materials and are then used for classification in a manner similar to any texture analysis and classification method. Based on our experimental results, it is found that the SID and TPS coefficients, in particular the TPS coefficients, are indeed good measure for the textural features corresponding to the shape-size-intensity distribution of the material grains in the micrographs. Hence our proposed method may be reliably used for material analysis, process control, etc.

The scheme described in this paper may be extended to some applications as follow.

1. *Material inspection*: The proposed method may be used for locating any defect, fault, presence of impurities, etc. in a material sample. The shape-size-intensity distribution of the material grains may be extracted by scanning the input sample thoroughly. Deviation from this distribution measure at any point in the sample will indicate defect or presence of impurity at that location.

2. *Material characterization*: The structure, size and color of the grains determine important physical properties of a material. For example, high aspect-ratio in grain size indicates good mechanical reinforcing effect. Materials composed of coarse sized grains generally detract from mechanical reinforcement, segregate and settle quickly, affect the processing and quality of end-use products, lead to higher abrasion, and affect surface finish. On the other hand, excessive amounts of fine grains can lead to ineffective mechanical reinforcement, high resin consumption as a filler, and problems with materials handling. Also, the density of a material may be assessed by evaluating the number of grain pixels in a micrograph. Similarly, distribution of grain intensity (or color) may be used to assess the concentration of different elements in an alloy.

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