ROAD SURFACE TEXTURES CLASSIFICATION USING OPENING-BASED IMAGE PROCESSING

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KEY WORDS: texture analysis, road surface inspection, hierarchical process, multiresolution cooccurrence matrix, morphological pyramid

ABSTRACT

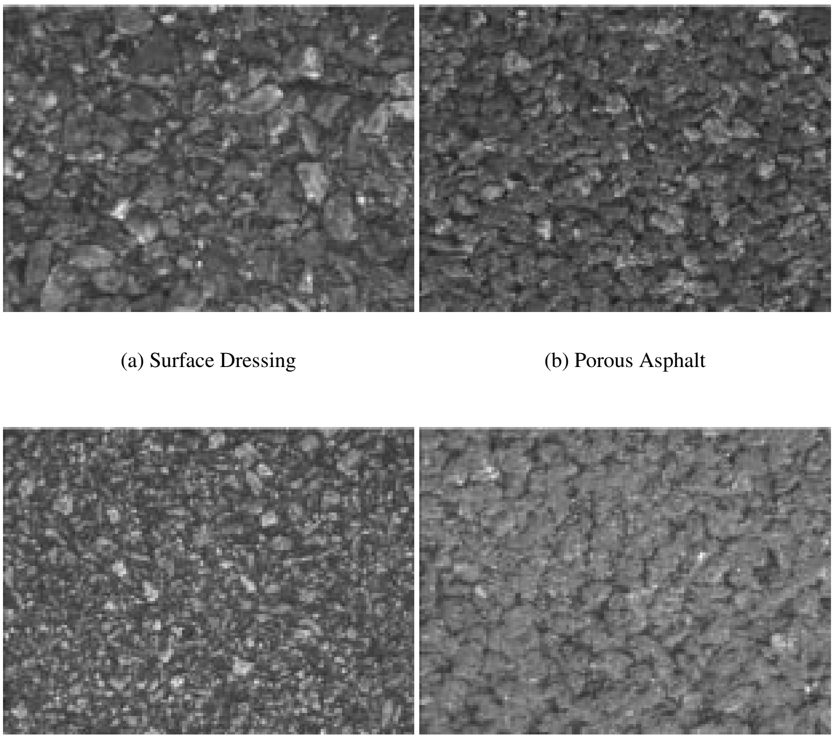
This paper deals with an innovative approach for achieving an automatic vision system for road surface texture classification. A road surface is composed by aggregates with a particular grain size distribution and the mortar matrix. From a vision point of view, road surface images can be described as a set of objects of high intensities puts on a low intensity uniform background. In image processing, mathematical morphology provides a set of tools used to compare parts of an image with structuring elements of various sizes and shapes. Information about objects can be obtained by applying successives openings with structuring elements of increasing sizes. Our aim is to characterize 4 road surface textures with different size and shape distributions. In order to avoid the choice of a set of structuring elements, we define an opening transformation based on quadtree approach. At each step, each non overlapping 2×2 blocks take one new grey level, corresponding to its lowest one. Variations of texture observed at each step are studied through an original cooccurrence matrix. Such a matrix is computed between two consecutive pyramid levels. Classification is carried out by extracting textural features from the set of matrices.

1 INTRODUCTION

Our work aim is to develop an image analysis method for road surface classification. Future tasks will be to locate texture inhomogeneities relative to pavement surface defects such as cracks. Road surface texture images can be described as objects of different size and shape put on an uniform background. In France, 98% of pavements are hydrocarbon concrete which can be divided into two categories : surface dressing (chipping on binder layer) and bituminous asphalt (mixtures of coarse aggregate, fine aggregate with or without filler, and hydrocarbon binder). There are several surface dressing (SD) conceptions but from a surface aspect point of view surface texture has a strong roughness level because of aggregates angularity ; however 3 classes of bituminous asphalt can be made considering their percentage of voids : dense, semi-dense and open, whose principal members are respectively classical bituminous asphalt (CBA), ultra-thin bituminous asphalt (UTBA) and porous asphalt (PA). Of course in a same pavement classe several grain size distributions can occur. An example of studied pavements is given in figure 1.

Multi-resolution pyramids are frequently used for detection and identification of objects or features of different size (Rosenfeld and Sher, 1988, Konik et al., 1993, Segall et al., 1999). In a general way, an images pyramid represents a collection of scene representation corresponding to an original image taken at low resolution. The data structure is initialised by placing the input image at the lowest level. The next levels are constructed by successively filtering and subsampling. The process finishes at the apex of the pyramid structure, when the last level is nonempty. Construction of images pyramid typically apply linear low- or pass-band filters. This technique removes all high frequency signal content, which alters the objects intensities and therefore induces region merging between successive levels. It is not suitable for tasks involving precise measurement of object size and shape. Morphological filters remove small features without altering high frequency information. These filters preserve essentiel shape characteristics while eliminating irrevelancies. By considering the nature of the road surface images, it is natural to use mathematical morphology, which deals directly with shape, as a basis for the construction of pyramid levels.

This paper proposes to apply opening-based processing to road surface classification problem. The outline of this paper is organized as follows : Section 2 reviews briefly mathematical morphological tools used to constructed morphological



(a) Surface Dressing (b) Porous Asphalt

(c) Bituminous Asphalt (d) Ultra Thin BA

Figure 1: Pavement surface families

filters. These morphological filters are used in section 3 to compute an original morphological pyramid. The following section presents the multiresolution cooccurrence matrix and its analysis to obtain a texture description. Section 5 gives classification procedure and some results.

2 MORPHOLOGICAL TOOLS

Mathematical morphology analyses the *geometrical structure of a set by probing and transforming its microstructure with different predefined elementary sets* (Toet, 1989), also called structuring elements. The two fundamental operations are *erosion* and *dilatation*. Dilatation removes low intensity regions. A function $f(x)$, dilated by a structuring element B, is defined as :

$$\forall x \in D \subseteq E^2, \quad (f \oplus B)(x) = \max_{y \in B}\{f(x+y)\}, \tag{1}$$

where $\oplus$ denotes dilatation, E is the set of integers and B a subset of E^2. Similarly, an erosion removes small regions of high intensity, and is defined as :

$$\forall x \in D \subseteq E^2, \quad (f \ominus B)(x) = \min_{y \in B}\{f(x-y)\}, \tag{2}$$

where $\ominus$ denotes erosion.

Morphological filters are used to build morphological pyramid in order to reduce information content by eliminating small objects or object protusions from high resolution and to produce a signal convenient for subsampling step (Haralick et al., 1987). Morphological filters are constructed by iterative application of erosion and dilatation. The most frequently used is the opening one, which consists of an erosion followed by a dilatation, defined as :

$$(f \circ B) = (f \ominus B) \oplus B, \tag{3}$$

where $\circ$ denotes the opening operation. In a general way, an operator ψ is defined as an opening if and only if the next 3 rules are checked (Serra, 1988) :

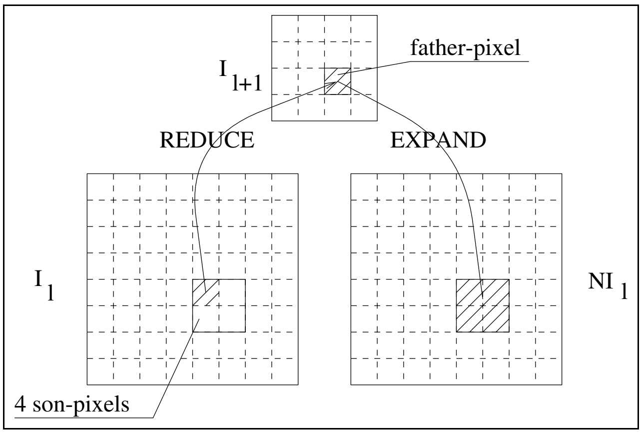


Figure 2: REDUCE and EXPAND operations. The lowest gray level ***son***-pixel used to build ***father***-pixel is represented by shaded area.

1. $\psi(X) \subseteq X$, anti-extensivity,
2. $X \subset Y \Rightarrow \psi(X) \subset \psi(Y)$, increasing,
3. $\psi \circ \psi = \psi$, idempotence

The last two rules mean, respectively, that ψ maintains inclusion relationships on the output image, and the result of the filter operation is unchanged when ψ is reapplied.

As one can imagine, the alteration of the input image by such a transformation is highly dependent upon the shape and the size of the structuring element. In practice, openings are used to obtain a structural decomposition of an image by using structuring elements of same shape but with increasing size. By this way, larger image details are filtered out. It gives a multidimensionnal analysis of the input texture usually called opening distribution.

3 MORPHOLOGICAL PYRAMID

The main drawback of morphological filters is the difficult choice of the appropriate structuring element needed to probe texture objects. To avoid this problem, we define an original morphological pyramid, whose conctruction is based on usual quadtree decomposition. The REDUCE process, which generates each image I_l from its predecessor I_{l-1}, is based on the set of non overlapping 2×2 pixels blocks extracted from I_l.

An important aspect for road surface characterisation is directly linked to low gray tone regions located in the wearing course. Our aim is to detect and identify background regions by rising up low gray levels through a morphological pyramid. The REDUCE operation is then definied as :

$$GL(I_l)(i,j) = \min\{GL(I_{l-1})(u,v)\}, \tag{4}$$

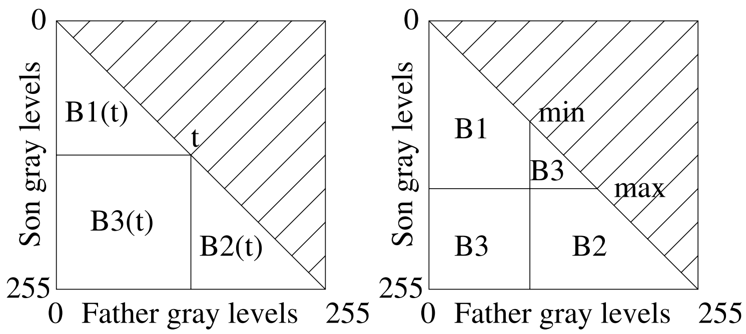
where $2i \leq u \leq 2i+1$ and $2j \leq v \leq 2j+1$.

Equation (4) means that for each non overlapping pixel blocks, only pixels having the lowest gray level value is taken into account. The min operator make REDUCE operation similar to an erosion step. Moreover, we can note that a pixel in I_l is linked to 4 *son*-pixels in I_{l-1} and to one and only one *father*-pixel in I_{l+1}. By this way, a hierarchical structure is then developped.

A reverse operation can be defined. EXPAND operation consists in expanding an image of size NxN to an image of size $2N$x$2N$. This step is realized by affecting to each *son*-pixel its *father*-pixel gray level. A new image is then constructed :

$$NI_l = EXPAND(I_{l+1}) \tag{5}$$

Operation ψ (see figure (2)), which consists in transforming image I_l into image NI_l is clearly anti-extensive, increasing and idempotent. So ψ is an opening and removes all small objects of high intensity and then rises up low gray levels related to background pixels.



(a) Matrix mapping for a threshold value t

(b) Matrix mapping for 2 threshold values $\min$ and $\max$

Figure 3: Gray level cooccurrence matrix mapping

4 TEXTURE ANALYSIS

4.1 Multiresolution cooccurrence matrix

Our approach is based on the idea of representing transition information between background and objects. The gray level cooccurrence matrix gives an overall idea about the spatial variations of gray levels in the texture image. This method consists of the computation of a matrix by counting the number of gray level occurrences of 2 pixels under predefined distance d and orientation θ. The most important drawback to characterize texture in an image is the choice of the best set of couples (d,θ), which will give the best texture description.

Morphological pyramidal inter-level links, previously described, allow us to compute a new cooccurrence matrix by considering gray level occurrences between a *son*-pixel taken at level l and its *father*-pixel at upper level $l + 1$. This configuration presents two interesting properties. Indeed, such a construction doesn't concern only relation between 2 pixels but it describes a relation between a pixel and one of its neighboring. Besides, the choice of an optimal couple (d,θ) is then discarded.

4.2 Data analysis

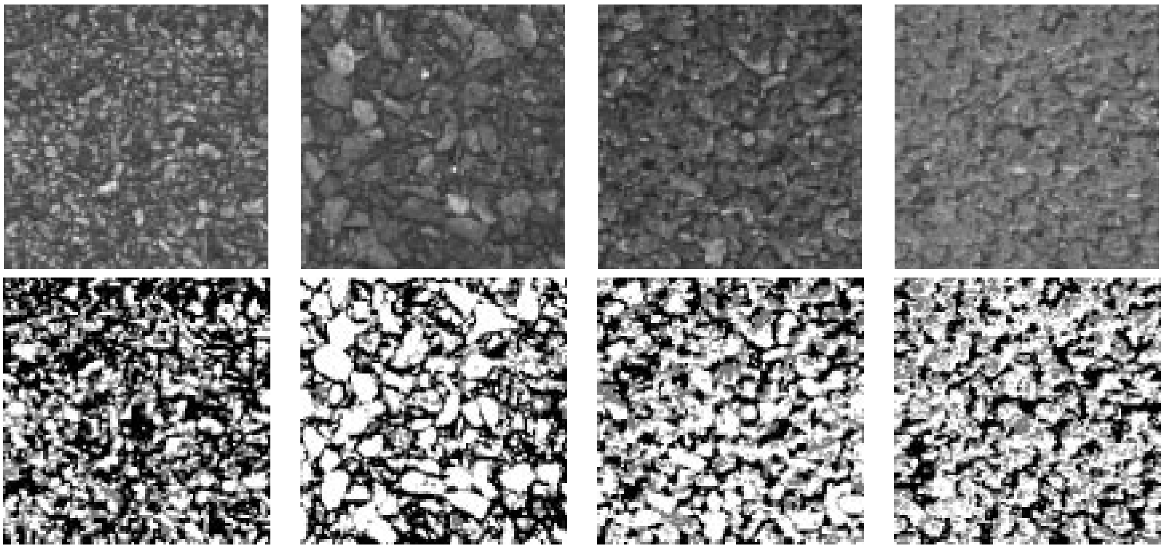
Texture description step is based on information extracted from multidimensionnal cooccurrence matrices computed by considering two successive morphological pyramid levels, l and $l + 1$. Let C be this one. C contains data types that can be divided into 2 categories.

4.2.1 Diagonal information Classical cooccurrence matrices valued on intensity images contain many information about regions (Chubb and Yellot, 2000). Data analysis can be done by studying matrix diagonal (Rouquet et al., 1996, Rouquet et al., 1998), which is relevant to texture homogeneity variation along pyramidal representation (Paquis et al., 1999).

By construction, such a distribution contains histogram of the image which is represented in level $l + 1$. Texture variation analysis is performed by extracting statistical parameters (skewness and kurtosis) from a residual distribution, which results from subtraction operation between matrix diagonal distribution and image histogram at level $l + 1$. In practice, we consider only the first 5 pyramid levels. So, a features vector $\overrightarrow{V} \in \overrightarrow{R^8}$ is obtained.

4.2.2 Matrix shape information Another way to extract features from cooccurrence matrix is to consider its shape (Haddon and Boyce, 1990, Houzelle and Giraudon, 1991, Tremeau et al., 1996). Let t be a threshold, which maps the original texture into a set of distinct regions : region R_0, corresponding to the uniform background and a set of regions R_i, representing objects of different intensities. Because of REDUCE operation, used to compute the morphological pyramid, matrix C is divided into 3 non-empty blocks as shown in figure 3.(a) :

$$\begin{cases} B1(t) : \text{coefficients which belong to the background of the input texture image} \\ B2(t) : \text{coefficients linked to the objects} \\ B3(t) : \text{coefficients linked to transition between background and objects} \end{cases}$$



CBA *SD* *PA* *UTBA*

Figure 4: Example of simplified road texture images obtained for each surface category (white pixels $\equiv$ Objects, black pixels $\equiv$ Background and grey pixels $\equiv$ Transitions).

The technique used for the selection of the threshold value t consists of evaluating the distribution of the cooccurrence matrix coefficients through a function, called *measure*. Principle lies in considering that Foreground/Background interaction is important when intensities of pairs of pixels are very different. Such information is located in block $B3$ merged in matrix. We apply 3 measures (Chanda and Majumder, 1988) on such a block to extract 3 possible threshold values. By taking into account $\min$ and $\max$ values, a new matrix mapping is obtained as shown in figure 3.(b). We can create a new image representation for level l, by assigning a label to each matrix regions.

This procedure is applied along our pyramidal structure and a new one is created, whose levels are quantified on 3 values corresponding to Object, Background and Transition. Simplified texture version is computed by using a *top/down* process, whose construction rule is :

1. If (Father = Object)
    - If (Son = Object) then Son = Object
    - If (Son = Background) then Son = Transition
    - If (Son = Transition) then Son = Object
2. If (Father = Background or Transition) then Nothing

Segmentation results are given in figure 4. A structural analysis of these segmented images is presented in the following section.

5 EXPERIMENTALS RESULTS

5.1 Procedure of classification

Procedure of classification is divided into 2 steps. Preclassification step consists in distinguishing SD/CBA class from PA/UTBA one. If we consider road texture from an aggregate arrangement point of view, we can note that only coarse aggregates appear on PA/UTBA surfaces, besides, background is visible partially. SD/CBA surfaces are composed by mixture of coarse and fine aggregates and background region is approximatively connex.

Distinction between these 2 categories is performed by analysing 2 components texture images extracted from the simplified texture. Objects number, N_O, is valued on *high* binary image obtained by affecting to each Transition pixels, the Objects label. Background number, N_B, is extracted from *low* binary image obtained by assigning to each Transition pixels the Background label. Separation is done by comparing N_O/N_B fraction to 1 :

IF $N_O/N_B > 1$ THEN SD/CBA class, ELSE PA/UTBA class

For each class, road surface texture is classified by analysing textural features extracted from residual distributions of multiresolution cooccurrence matrices. For each unknown texture, a parameters vector $\overrightarrow{V} \in \overrightarrow{R^8}$ is computed. Classifiction consists in comparing this features vector to a set of reference vectors. We compare Mahalanobis measures between candidat and kernels simply.

5.2 Application

Our classification algorithm was applied to a set of 60 samples (15 per familly). These texture were digitized on tests tracks of LCPC (Nantes) with a 768×572 spatial resolution, quantified on 256 grey levels. All manipulations were done on dry pavement surfaces without distress features.

Each image was divided into 5 overlapping 512×512 subimages. Among them, the corresponding center one was used as training set to estimate reference vectors nessecary to the second classification step. Remaining 4 subimages of each texture, 240 subimages altogether, were taken as an unknown set to be classified.

The classification results are listed in table 5.2, which represents confusion matrix $Conf(\alpha_i, \alpha_j)$ where each entry gives percentage of elements belonging to the class α_i assigned to the class α_j.

	CBA	SD	PA	UTBA
CBA	90	10	0	0
SD	0	97	3	0
PA	0	0	100	0
UTBA	0	0	0	100

Table 1: Classification results of 240 subimages from 4×15 road surface texture images.

Approach was also applied to a set of 200 new subimages from 4×10 images. We used the same training set as the one defined previously. Classification results are shown in table 5.2.

	CBA	SD	PA	UTBA
CBA	100	0	0	0
SD	0	88	12	0
PA	0	2	98	0
UTBA	0	0	0	100

Table 2: Classification results of 200 subimages from 4×10 new road surface texture images.

6 CONCLUSION

This paper has presented an image processing tool for achieving classification task of 4 categories of road surfaces textures. Developped method is based on a non linear image transformation similar to a classical opening operator. This operation allows to study image textures at several scales. Texture analysis step is based on information extracted from data of a set of multiresolution cooccurrence matrix. The classification schem combines 2 complementary steps : a statistical one, which values texture variation along the multi-scale decomposition, and a structural one, where a simplified texture version is analysed geometrically.

First results of such a classification method are interesting and further work would consist in testing this approach on a larger set of road surface texture images. Besides it woud be interesting to use this procedure to locate inhomogeneities in texture in order to detect pavement surface defects.

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