Pattern Recognition Letters
journal homepage: www.elsevier.com

An appendix to "Texture databases – A comprehensive survey"

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ARTICLE INFO

Article history:

Texture
Database
Bio-medical images
Materials

ABSTRACT

Texture analysis is an area of intense research activity. Like in other fields, the availability of public data for benchmarking is vital to the development of the discipline. In "Texture databases – A comprehensive survey", Hossain and Serikawa recently provided a precious review of a good number of texture datasets, and put an order into this scattered field. The aim of this appendix is to complement the cited work by providing reference to additional image databases of bio-medical textures, textures of materials and natural textures that have been recently employed in experiments with texture analysis. There is in fact a good number of little-known texture databases which have very interesting features, and for this reason are likely to receive increasing attention in the near future. We are convinced that this extension, along with the original article, will be useful to many researchers and practitioners working in the field of texture analysis.

1. Introduction

Texture analysis has been an area of intense research activity for at least forty years. As a fundamental feature of images, texture plays a central role in many machine vision applications: surface sorting and grading, defect detection, content-based image retrieval, computer-assisted diagnosis, object tracking and face recognition are just some examples.

The selection of a proper set of images for experimenting with texture descriptors is a typical problem in this field. We believe it is no exaggeration to state that any researcher working on texture analysis has at least once in his career faced with the following question 'which dataset(s) should I use in my experiments?'. For the benefit of those readers concerned with this matter, Hossain and Serikawa (2013) have recently surveyed a set of texture databases in the field of medical imaging, natural textures, textures of materials and dynamic textures. It is the aim of this paper to complement their precious work by covering an additional set of texture databases that did not find a place in the cited reference. Along with the celebrated Brodatz, CUReT, OuTex, VisTex, and so on – already reviewed by Hossain and Serikawa (2013) – there are in fact quite a few texture databases which, despite their being scarcely known, have very interesting features and are therefore likely to receive increasing attention in the near future. Our review is limited to those datasets that are open-access and free for research and non-commercial activities. Commercial databases are not considered in this study.

In the remainder the texture databases are divided into three groups: bio-medical textures (Sec. 2), natural textures (Sec. 3) and textures of materials (Sec. 4). There is no section for dy-

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namic textures, since they have been exhaustively covered in the cited reference. We conclude the paper with a thorough discussion on the subject (Sec. 5) followed by some final considerations (Sec. 6).

2. Bio-medical textures

In the bio-medical field, the amount of digital images generated for diagnostic and therapeutic purposes is increasing steadily (Oberoi et al., 2013). Unfortunately, as Kauppi et al. (2013) recently noted, most data are not public, therefore it is difficult to carry out large experimental comparisons and state-of-the art surveys. In this section we review eight datasets from different bio-medicals areas. The specific properties of each dataset, like signal source and additional information, are summarised in Tab. 1.

Table 1. Bio-medical textures: properties of the databases.

Dataset	Signal source	Additional information
CT emphysema	X-rays	Res.: 0,78 × 0,78 mm Thickness: 1,25 mm Voltage: 1,25 kV Current: 200 mAs
Epistroma	Light microscopy	Magnification: 20×
IICBU ‘Binucleate’	Fluoresc. microsc.	Magnification: 60×
IICBU ‘Lymphoma’	Light microsc.	–
IICBU ‘Liver’	Light microsc.	Magnification: 40×
Mammographic (12er)	X-rays	–
Mammographic (20er)	X-rays	–
MESSIDOR	Digital ophthalmosc.	–

2.1. *Computed-tomography emphysema database*

This database includes 115 high-resolution computed-tomography (HRCT) slices and 168 image patches manually selected and annotated from them (CT-Emphysema, 2008). Of the two groups the latter is mainly composed of stationary texture images (Fig. 1) and is therefore the most relevant to this study. Each patch is classified as either normal tissue, centrilobular emphysema or paraseptal emphysema. The patches are provided as grey-scale 16 bit tiff images with a resolution of 61 × 61 pixels. The dataset has been the basis for testing the effectiveness of some texture descriptors in this field (Gangeh et al., 2011; Sørensen et al., 2010).

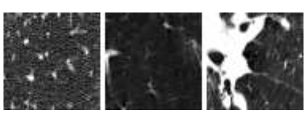

Fig. 1. The three classes of the computed-tomography emphysema database (patches): *Normal tissue*, *centrilobular emphysema* and *paraseptal emphysema*.

2.2. *Epistroma*

The Epistroma database (Epistroma, 2012) is based on a set of tissue samples taken from a series of 643 patients with histologically-verified colorectal cancer at the Helsinki University Central Hospital, Helsinki, Finland, from 1989 to 1998 (Linder et al., 2012). The dataset contains 720 png 24 bit colour images of variable resolution cropped from digitized micro-array array slides of the patients' tissue. Each image is labelled as belonging to one of the following two classes: epithelium or stroma (Fig. 2). The dataset has been recently used to prove the feasibility of texture analysis for automated identification of epithelium and stroma in tumor tissue micro-arrays (Linder et al., 2012).

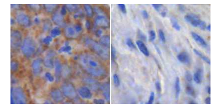

Fig. 2. The two classes of epistroma database: *epithelium* and *stroma*.

2.3. *IICBU Biological Image Repository*

The IICBU Biological Image Repository database was proposed as a benchmark for testing and comparing the performance of image analysis algorithms for biological imaging (Shamir et al., 2008). The whole database is composed of 11 subsets representing different classification problems and image types of which the datasets ‘Binucleate’, ‘Lymphoma’, ‘Liver gender (CR)’, ‘Liver gender (AL)’ and ‘Liver aging’ are particularly rich in texture images. The first includes 16 bit grey-scale tiff images of resolution 1280 × 1024 pixels from two classes: binucleate and non-binucleate cellular phenotypes (Fig. 3).

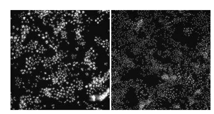

Fig. 3. The two classes of the IICBU ‘Binucleate’ database: *Binucleate* and *Non-binucleate*

The second contains 24 bit colour tiff images of resolution 1388 × 1040 pixels from three classes representing different types of malignant lymphoma (Fig. 4): chronic lymphocytic leukaemia (CLL), follicular lymphoma (FL) and mantle cell lymphoma (MCL).

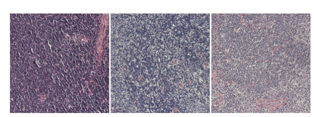

Fig. 4. The three classes of the IICBU ‘Lymphoma’ database: *chronic lymphocytic leukaemia*, *follicular lymphoma* and *mantle cell lymphoma*

The three ‘Liver’ subsets represent slices of liver organs extracted from sacrificed mice, stained with haematoxylin and eosin, and imaged through a bright-field microscope (Fig. 5). The resulting 48 bit colour tiff images (resolution: 1388 × 1040 pixels) are labelled across three axes of differentiation: age (1, 6, 16 and 24 months), gender (male/female) and diet (ad-libitum/caloric restriction).

Recent references where the datasets described in this section have been used to test texture descriptors are the works of Huang et al. (2013); Hervé et al. (2011); Orlov et al. (2010).

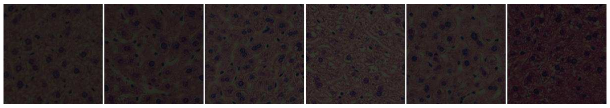

Fig. 5. Samples from the IICBU 'Liver' databases (age/gender/diet): *1/female/ad-libitum*, *6/female/ad-libitum*, *24/female/ad-libitum*, *1/male/ad-libitum*, *16/male/ad-libitum* and *6/male/caloric restriction*

2.4. Mammographic patches

This database is the result of a project aiming at the development of a standard reference for computer-aided mammography. It is a recollection of mammographic patches from screening mammography taken from different sources (de Oliveira et al., 2008). Previously selected and annotated patches are provided as 16 bit grey-scale png with a resolution of 128 × 128 pixels. The database is organised in two sub-databases of 12 (Fig. 6) and 20 classes, respectively. In both cases the patches are pre-classified according to the BI-RADS classification system (The American cancer society, 2013), which is based on breast density (values from I to IV, where I stands for entirely fat; IV for extremely dense) and category of lesion (values from 1 to 6, where 1 stands for negative; 6 for biopsy-proven malignancy). Both datasets have been recently used for testing texture features in computer-aided diagnostics and image retrieval (de Oliveira et al., 2010; Deserno et al., 2012).

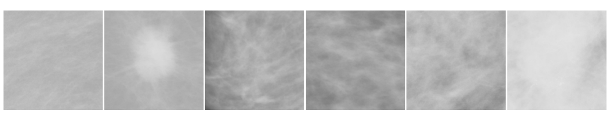

Fig. 6. Samples from the 12er mammographic patches database (breast density/category of lesion): *I/1, I/5, II/1, III/1, IV/1* and *IV/5*. Courtesy of T.M. Deserno, Dept. of Medical Informatics, RWTH Aachen, Germany.

2.5. MESSIDOR

MESSIDOR (Méthodes d'Evaluation de Systèmes de Segmentation et d'Indexation Dédiées à l'Ophtalmologie Rétinienne) is a database of 1200 digital images of eye fundi (Fig. 7) acquired within the ophthalmologic departments of the following three medical institutions (MESSIDOR, 2005). The images have been acquired with a colour video 3-CCD camera and are presented as 24 bit colour tiff with variable image resolution: 1440 × 960, 2240 × 1488 or 2304 × 1536 pixels. Each image is classified according to two different attributes: retinopathy grade (four classes, from 0 to 3 in ascending order of severeness – 0 = normal) and risk of macular oedema (three classes, from 0 to 2 in ascending order of severeness – 0 = normal). The combination of the two attributes therefore gives 12 possible classes. Both regions of interest (Deepak et al., 2012) and full-size images (Oberoi et al., 2013) from MESSIDOR have been recently used as a basis for evaluating texture analysis algorithms.

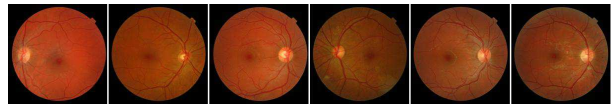

Fig. 7. Samples from the MESSIDOR database (retinopathy grade/risk of macular oedema): *0/0, 1/0, 2/0, 2/1, 2/2, 3/1*. Kindly provided by the Messidor program partners (see http://messidor.crihan.fr).

3. Natural textures

Following the categorisation proposed by Hossain and Serikawa (2013), the three datasets included in this section are composed of heterogeneous texture classes mostly dominated by general outdoor scenes like buildings, vegetation, walls, plants, etc. A common feature of the three datasets is that the images have been acquired under uncontrolled illumination and viewing conditions.

3.1. Mayang's texture library

Mayang's textures[1] latest version (16) is a huge project containing 4350 images from the following nine macro-classes: architectural, buildings, fabric, man-made, metal, nature, plants, stone and wood (Fig. 8). The images have been acquired with different cameras and under uncontrolled illumination and viewing conditions. The resolution is also variable, ranging from 2 to 18 MPixels.

Fig. 8. Samples from Mayang's dataset: *Architectural/brick*, *Food/melon*, *Metal/patterned metal/cross hatch* and *Wood/bark*.

3.2. Salzburg texture image database (STex)

The Salzburg texture image database (STex) is a project maintained by the Multimedia Signal Processing and Security Lab, at the University of Salzburg, Salzburg, Austria (STex, 2009). The dataset contains 476 colour texture images captured around the city of Salzburg. Each image corresponds to a different class such as bark, fabric, gravel, stone, wall, etc. (see Fig. 9). The images are provided as 24 bit colour pnm with a resolution of 1024 × 1024 pixels.

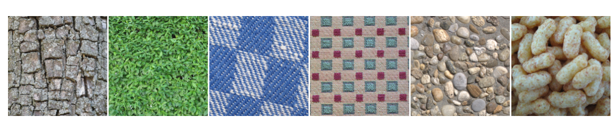

Fig. 9. Samples from the Salzburg texture image database: *Bark.0004*, *Bush.0000*, *Fabric.0009*, *Fabric.0055*, *Floor.0003* and *Food.0008*.

[1]The free version of the library has a download limit of 20 textures/day.

3.3. USPTex

The USPTex dataset (USPTex, 2012) includes 191 classes of general scenes like roads, vegetation, walls, clouds, gravel and the like, as well as materials such as seeds, rice, tissues, etc. – see Fig. 10. The database is maintained by the Scientific Computing Group at the Universidade de São Paulo, São Paulo, Brazil. Each class is represented by 12 samples provided as 24 bit colour png images with a resolution of 128 × 128 pixels. The dataset has been referenced in recent works on texture analysis algorithms (Backes et al., 2012; Florindo and Bruno, 2012).

Fig. 10. Samples from the USPTex dataset: *c002*, *c003*, *c017*, *c069*, *c071*, and *c114*.

4. Textures of materials

In this section we present nine databases of texture images representing real-life materials. Some datasets include one type of material only, such as wood (Secs. 4.3 and 4.7), granite (Sec. 4.6) and ceramics (Sec. 4.8); the others contains different natural, and man-made materials. In table 2 we summarise the conditions under which the images have been acquired. In the table the term 'viewing direction' refers to the orientation of the optical axis of the camera with respect to the normal vector of the material's surface; 'rotation' indicates any rotation around such axis – also referred to as *roll* (Hill, 2001), and 'scale' any change in the object-camera distance or in the optical zoom (which provokes a change in the objects' dimensions).

Table 2. Textures of materials: properties of the databases.

Dataset	Illum.	Viewing dir.	Rot.	Scale
BTF Bonn 'ATRIUM'	V, C	V, C	No	No
BTF Bonn 'UBO2003'	V, C	V, C	No	No
Drexel	V, C	V, C	Yes, C	Yes, C
Forest species	F	F	No	No
Jerry Wu	V, C	F	Yes, C	No
Kylberg Sintorn	F	F	Yes, C	No
MondialMarmi	F	F	Yes, C	No
Parquet	F	F	No	No
VxC TSG	F	F	No	No

Note: V = variable, C = controlled, F = fixed

4.1. BTF Database Bonn

BTF Database Bonn is part of a wide research project developed and maintained by the Institute of Computer Science II at the University of Bonn, Bonn, Germany (Müller et al., 2005). It currently includes five image datasets, of which two are particularly rich in texture: 'ATRIUM' (Fig. 11) and 'UBO2003' (Fig. 12). They contain six and four classes of materials, respectively. Each material sample has been acquired under 81 different viewing and lighting conditions, giving 81 × 81 = 6561 images for each class. Image resolution is 256 × 256 for dataset 'UBO2003' and 800 × 800 for dataset 'ATRIUM'. The BTF database has been included in recent experimental works on texture analysis (Fernández et al., 2013; Paci et al., 2013).

Fig. 11. The four classes of the BTF database Bonn 'ATRIUM': *Ceiling*, *Floortile*, *Pinktile* and *Walkway*.

Fig. 12. The six classes of the BTF database Bonn 'UBO2003': *Corduroy*, *Impalla*, *Proposte*, *Pulli*, *Wallpaper* and *Wool*.

4.2. Drexel texture database

The Drexel Texture Database, proposed by the Drexel Vision Group at Drexel University, Philadelphia, USA, includes 20 classes of different materials such as bark, sandpaper, sponge, etc. – see Fig. 13. Each material has been acquired under different and controlled conditions of illumination, distance, rotation and viewing direction (Oxholm et al., 2012). Textures are provided as high-dynamic-range (HDR) colour images with a resolution of 128 × 128 pixels.

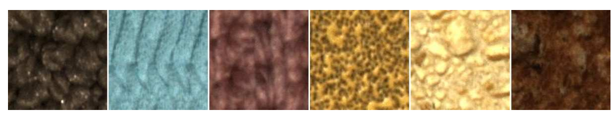

Fig. 13. Samples from the Drexel texture database: *Carpet1*, *Cloth2*, *Knit2*, *Sandpaper*, *Sponge* and *Toast2*.

4.3. Forest species database

The forest species database (Fig. 14), maintained by the Laboratory of Wood Anatomy at the Federal University of Paraná at Curitiba, Brazil, contains microscopy images of 112 different forest species (Martins et al., 2013). The database has been acquired from previously stained and dehydrated slices of wood using an Olympus C×40 microscope with 100× magnification. The resulting images are available as 24 bit colour png with a resolution of 1024 × 768 pixels. Thirty-seven of the 112 available species are softwoods and the remaining 75 are hardwoods. The two groups are further subdivided into 23 genera and eight families, and 62 genera and 22 families, respectively.

4.4. Jerry Wu photometric image database

The Jerry Wu photometric image database (Jerry Wu, 2003) is a project maintained within the TextureLab at Heriot-Watt University, Edinburgh, UK. The database is named after Dr. Jerry Wu, who developed it as a part of his Ph.D. The database

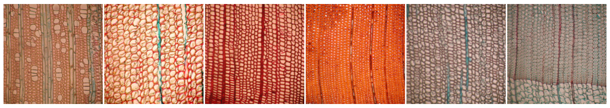

Fig. 14. Samples from the forest species database: *Magnolia grandiflora*, *Araucaria angustifolia*, *Calocedrus decurrens*, *Cedrus libani*, *Gingko biloba* and *Larix lariciana*.

contains 39 textures of rough surfaces (Fig. 15) of unspecified materials acquired under different viewing and illumination conditions. The images are provided as 8 bit grey-scale bmp-with a resolution of 512 × 512 pixels[2]. Various authors have employed this dataset for benchmarking texture analysis algorithms (Fernández et al., 2013, 2011; Nurzyńska et al., 2013; Kononenko and Bevk, 2009).

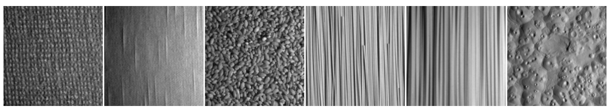

Fig. 15. Samples from Jerry Wu's photometric texture database: *an1*, *an5*, *bn2*, *di1*, *nd1* and *rks1*.

4.5. Kylberg Sintorn Rotation Dataset

The Kylberg Sintorn Rotation Dataset (Kylberg-Sintorn, 2013) includes 25 classes of materials such as fabric, grains, sugar, rice, etc (Fig. 16). The original images (one for each class) are 32 bit colour png with a resolution of 5184 × 3456 pixels. The dataset provides hardware- and software-rotated images at 10 rotation angles: 0°, 40°, 80°, 120°, 160°, 200°, 240°, 280° and 320°. Other conditions such as illumination, viewing direction and scale are invariable.

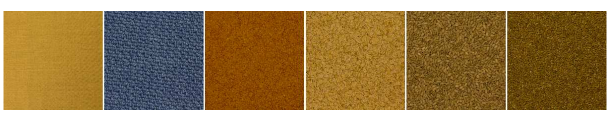

Fig. 16. Samples from the Kylberg Sintorn rotation dataset: *Canvas01*, *Knitwear01*, *Lentils01*, *Oatmeal01*, *Seeds01* and *Wheat01*.

4.6. MondialMarmi

MondialMarmi is a database of granite images containing, in the current version (1.1), 12 classes representing commercial types of granite (Fig. 17). The project is maintained by the Department of Industrial Engineering at the Università degli Studi di Perugia, Perugia, Italy. The database contains four images for each class; each image corresponds to one granite tile. The images are 24 bit colour bmp with a resolution of 544 × 544 pixels. MondialMarmi includes both hardware- and software-rotated images at nine rotation angles: 0°, 5°, 10°, 15°, 30°, 45°, 60°, 75° and 90°. Scale, viewing direction and illumination conditions are invariable. This dataset has been used in recent works for comparing texture analysis algorithms (Paci et al., 2013; Kylberg and Sintorn, 2013; Fernández et al., 2013; Bianconi et al., 2012).

Fig. 17. Samples from the MondialMarmi dataset: *Acquamarina*, *Azul Platino*, *Bianco Sardo*, *Giallo Ornamentale*, *Giallo Veneziano* and *Rosa Porriño A*.

4.7. Parquet image databse

The Parquet image database includes 14 classes of engineered wood (Fig. 18) representing different types of commercial parquet (Parquet, 2012). Each class includes from two to four different subclasses (tones) with minimal colour and texture difference from each other. The dataset contains a total of 295 images with a number of image samples for each tone variable from six to eight. The images are provided as 24 bit colour bmp with resolution variable from class to class. Rotation, scale, viewing direction and illumination conditions are invariable. The database has been recently employed to compare the effectiveness of machine vision algorithms for surface grading (Bianconi et al., 2013).

Fig. 18. Samples from the Parquet image database: *IRK_01*, *OAK_02*, *OAK_04*, *OAK_10*, *OAK_11* and *TEK_01*.

4.8. VxC TSG image database for surface grading

The VxC TSG database (VxC TSG, 2005) is composed of 14 different classes of commercial tiles taken from the ceramic industry (Fig. 19). The database is provided by the Grup de Visió per Computaor (Computer Vision Group) at the Universitat Politécnica de Valencia, Valencia, Spain. Similarly to the Parquet database (Sec. 4.7) each class includes three different subclasses (grades) with minimal difference from each other (López et al., 2008). The number of samples for each class is variable, ranging from 14 to 30. The image resolution also differ considerably from class to class.

Fig. 19. Samples from the VxC TSG database: *Agata*, *Antique*, *Oslo*, *Somport*, *Vega* and *Venice*.

[2] Actually the images are 24 bit with eight bits per channel – but the three channels are redundant

Table 3. General properties of the texture databases – summary table.

Database	Image res.	No. of classes	Image format	Reference
Bio-medical textures				
CT emphysema database (patches)	61×61	3	16 bit grey-scale tiff	CT-Emphysema (2008)
Epistroma	Variable	2	24 bit colour png	Epistroma (2012)
IICBU ‘Binucleate’	1280×1024	2	16 bit grey-scale tiff	IICBU (2008)
IICBU ‘Lymphoma’	1388×1040	2	24 bit colour tiff	IICBU (2008)
IICBU ‘Liver’	1388×1040	11	48 bit colour tiff	IICBU (2008)
Mammographic patches (12er)	128×128	12	16 bit grey-scale png	MammoPatches (2012)
Mammographic patches (20er)	128×128	20	16 bit grey-scale png	MammoPatches (2012)
MESSIDOR	Variable	12	24 bit colour tiff	MESSIDOR (2005)
Natural textures				
Mayang	Variable	4350	24 bit colour jpg	Mayang (2001)
STex	1024×1024	476	24 bit colour pnm	STex (2009)
USPTex	128×128	191	24 bit colour png	USPTex (2012)
Textures of materials				
BTF Bonn ‘ATRIUM’	800×800	4	24 bit colour jpg	BTF-Bonn (2003)
BTF Bonn ‘UBO2003’	256×256	6	24 bit colour jpg	BTF-Bonn (2003)
Drexel	128×128	20	Colour HDR	Drexel (2012)
Forest species	1024×768	112	24 bit colour png	Forest species (2013)
Jerry Wu	512×512	39	8 bit grey-scale bmp	Jerry Wu (2003)
Kylberg Sintorn	5184×3456	25	32 bit colour png	Kylberg-Sintorn (2013)
MondialMarmi	544×544	12	24 bit colour bmp	MondialMarmi (2011)
Parquet	Variable	14+	24 bit colour bmp	Parquet (2012)
VxC TSG	Variable	14+	24 bit colour bmp	VxC TSG (2005)

Note: symbol ‘+’ indicates that each class includes two or more sub-classes.

5. Discussion

In this appendix we have summarised the main features of 20 texture databases, with particular attention to the imaging conditions, which play an important role when it comes to testing the robustness of texture descriptors against noise factors like changes in scale, rotation and viewing direction. Particularly interesting, to this end, is the recently proposed Drexel texture database, which presents 20 texture classes under several different yet controlled viewing and illumination conditions. BTF Bonn ‘ATRIUM’ and ‘UBO2003’ also feature variable illumination and viewing directions, but include fewer classes. Mayang, STex and USPTex excel in terms of the number of classes, providing 4350, 476 and 191, respectively.

We agree with other authors (Kauppi et al., 2013; Hossain and Serikawa, 2013) who affirm that the situation is somewhat critical in the field of bio-medical textures: the number of publicly available datasets is indeed very limited in this area. Considering the importance of the potential applications in this field, we strongly agree with those authors calling for open repositories of standardized case data and ground truth information (Deserno et al., 2012).

A final remark is about the availability of test-suites. These are collections of classification/segmentation problems with predefined subdivisions into training and validation sets (Ojala et al., 2002). Test-suites make it possible to execute experiments in a ‘standardised’ manner, this way enabling meaningful comparisons of texture analysis algorithms. At present we are aware of no test suites associated with the texture databases presented in this appendix. It is to be hoped that this gap will be filled in future works.

6. Conclusions

The availability of suitable image databases for benchmarking is widely acknowledged as a central issue in computer vision. Hossain and Serikawa (2013) have recently put some order in this panorama by providing a survey of texture databases. In this appendix we have tried to complement their work by presenting some additional datasets that did not find a place in the cited work. We believe that this extension, along with the original article, will be useful to many researchers and practitioners working in the field of texture analysis.

7. Acknowledgements

This work was partially supported by the the European Commission under project LIFE12-ENV/IT/000411 and by the Spanish Government under projects TRA2011-29454-C03-01 and CTM2010-16573.

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