Pattern Recognition Letters 34 (2013) 2007–2022

Contents lists available at SciVerse ScienceDirect

Pattern Recognition Letters

journal homepage: www.elsevier.com/locate/patrec

Texture databases – A comprehensive survey

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ARTICLE INFO

Article history:
Available online 26 February 2013

Keywords:
Texture
Database
Dynamic
Vision
Image

ABSTRACT

Texture analysis is a very important area in the field of computer vision and related fields. There are a good number of databases developed by different research groups for various texture analysis, in the field of medical analysis, robotics, recognition, analysis, image processing, etc. However, till-to-date, there is no comprehensive works covering the important databases and analyze these in various perspectives. In this paper, we consider this important task so that it becomes helpful for a researcher to choose and evaluate having crucial evaluating aspects in mind. We categorize and critically survey based on many references of the state-of-the-art related to the databases and other texture works. We strongly believe that this elegant survey will be a great contribution for the vision community, especially in the arena of texture analysis.

1. Introduction

Texture is one of the significant characteristics used in identifying objects of interest or regions in an image (Alam and Faruqui, 2011). Texture is an important characteristic of surface property in visual scenes and is a power cue in visual perception (Zhu et al., 1997). It is considered as an assemble of images of similar texture appearances. Texture analysis has various applications in different areas on computer vision, image processing, medical image processing and related fields. There is no clear-cut definition for image texture. Image texture is believed to be a rich source of visual information – about the nature and 3D shape of physical objects (Materka and Strzelecki, 1998). Textures are complex visual patterns composed of entities, or sub-patterns – that have characteristic brightness, color, slope, size, etc. Hence, texture can be regarded as a similarity grouping in an image (Rosenfeld and Kak, 1982). The local sub-pattern properties give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation, etc., of the texture as a whole (Materka and Strzelecki, 1998). In another definition, the texture of images refers to the appearance, structure and arrangement of the parts of an object within the image (Castellano et al., 2004). Smarter extraction of features from image textures produce better cues for image analysis, which are pivotal for object recognition, surface analysis, action recognition, disease diagnosis, etc. There are various approaches for texture analysis. Most of these approaches are based on structural, model-based, statistical (e.g., histogram, absolute gradient, run-length matrix, co-occurrence matrix, auto-regressive model, wavelets) and transform methods (Castellano et al., 2004). These approaches are compared and evaluated upon various datasets, some of these become well-known due to their availability and assessment by researchers.

Though there are a number of texture datasets, till-to-date, there is no comprehensive works covering the important databases and analyzing these in various perspectives. The demand for a thorough review on texture datasets is attended in this paper, so that it becomes helpful for a researcher to choose and evaluate having crucial evaluating aspects in mind.

Various datasets on texture are categorized and critically surveyed. We categorize them into the following four areas, namely texture databases in medical imaging; natural texture image database; texture of materials database' and dynamic texture database. Our strongly believe that this work will be a great contribution for the vision community, especially in the arena of texture analysis. The paper is organized as follows. Section 2 presents the datasets related to medical imaging. In Section 3, natural texture image datasets are covered. Datasets related to texture of various materials are discussed in Section 4. This is the largest group of datasets from various groups. The final category is the dynamic texture dataset which is categorized in Section 5. An overall comparative discussion with Tables is presented in Section 6. The paper is concluded in Section 7.

2. Texture databases in medical image processing

A significant amount of research has been done in the field of texture analysis in medical image segmentation (Roula et al., 2002; Keller et al., 1989; Harder et al., 2006; Sutton and Hall, 1972; Kovalev et al., 2001). The analysis of texture parameters is a useful way of increasing the information obtainable from medical

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http://dx.doi.org/10.1016/j.patrec.2013.02.009

images. It has various applications ranging from the segmentation of specific anatomical structures and the detection of lesions, to differentiation between pathological and healthy tissue in different organs, and texture analysis from radiological images (Castellano et al., 2004). Under this area, the important datasets are presented below:

2.1. MRI brain database

Forty-three volumetric MRI-T1 brain dataset is developed from 28 patients and 15 controls. This dataset is obtained on a 1.5-T Siemens scanner (MPRAGE sequence, TR 11.4 ms, TE 4.4 ms, 128 slices, matrix 256×256, voxel size $0.9 \times 0.9 \times 1.5$ mm). In this case, patients are diagnosed clinically as either suffering from WM encephalopathy and/or Alzheimer's disease, while controls are 15 healthy elderly individuals. Images are interpolated to an isotropic resolution of 1 mm and aligned with the stereo-tactical coordinate system using fourth-order b-spline interpolation tested additionally on the large sample of 210 MRI-T1 brain datasets of young healthy subjects including 103 male (group A) and 107 age-matched female (group B) with average age of 24.8 years and standard deviation of 3.9 years in the same way (Kovalev et al., 2001; Kruggel and von Cramon, 1999).

2.2. USF Database or Digital Database for Screening Mammography (DDSM)

Refs. Bozek et al. (2009), Alam and Faruqui (2011), Abdalla et al. (2011), Bandyopadhyay (2010), Bandyopadhyay and Maitra (in press), Zwiggelaar and Boggis (2001) use the Digital Database for Screening Mammography (DDSM) or USF database by Heath et al. (2000). The database (Heath et al., 2000) contains approximately 2620 cases. In each of the case, two images of each breast, associated patient information like age, stage of the tumor, subtlety rating for abnormalities, American College of Radiology (ACR) breast density rating are studied. The mammograms are digitized by various scanners depending on the source of the data. These images are available with the specification of 3000×4500 pixels with 16-bit pixel depth. One hundred mammographic images from the Digital Database for Screening Mammography (DDSM) (Heath et al., 2000) are exploited by Karahaliou et al. (2006). These are digitized with a LUMISYS 300 scanner at 12-bit pixel depth and spatial resolution 50 μm.

All mammograms selected correspond to heterogeneously and extremely dense breast parenchyma (density 3 and 4 according to the ACR BIRADS^{TM} lexicon) and contain subtle microcalcification (MC) clusters. There are 46 benign and 54 malignant clusters according to the database ground truth tables. Ref. Karahaliou et al. (2006) considers regions of interest of 128×128 pixels, containing the MCs, and these are employed for texture analysis.

2.3. Others in medical analysis

A significant amount of research has been done in the field of texture analysis in medical image segmentation, e.g., in (Roula et al., 2002; Keller et al., 1989; Harder et al., 2006; Sutton and Hall, 1972; Kovalev et al., 2001; Alam and Faruqui, 2011). Kovalev et al. (2001) demonstrates the use of multi-sort-co-occurrence matrices on MRI brain datasets. Karkanis et al. (1999) classify regions containing cancers in colonoscopy images. They use a multi-layer feed-forward neural network, which is based on second order gray-level statistics. Two different types of colonoscopic images are taken from two different colons in this experiment (i.e., macroscopically a Type IIIs lesion, which is hitologically a *low grade cancer*; and macroscopically a Type V lesion that is Histologically a *moderately differentiated carcinoma*). The images are digitized to a size of 2000×2000 pixels with 64 gray levels depth per pixel. Textures from 10 normal and 10 abnormal tissue samples, corresponding to a 256×256 image window, have been randomly chosen from each image (Karkanis et al., 1999).

3. Natural texture image database

This is the second category of texture image database where natural images are dominant in terms of image classes in these datasets. In Section 4, we present texture datasets of materials and we will find that there are some overlapping in both types. However, the Brodatz dataset is purely based on natural texture images. We find that some datasets are created at the top of another dataset. For example, the USC–SIPI (University of Southern California–Signal and Image Processing Institute) Texture Mosaics dataset is based on the Brodatz dataset.

3.1. Brodatz texture database

The Brodatz texture database or album is the most famous the most widely used dataset in the texture analysis (Keller et al., 1989; Sutton and Hall, 1972; Brodatz, 1966; Zhang et al., 2007; Ojala and Pietikainen, 1999; Beliakov et al., 2008; Greenspan et al., 1994; Rubner and Tomasi, 1999; Montoya-Zegarra et al., 2007; Peteri and Huskies, 2005; Lazebnik et al., 2005; Zhang et al., 2006; Ojala et al., 2001; Xu et al., 2006; Targhi et al., 2008; Caputo et al., 2005; Cula et al., 2004; Han and Perlin, 2003; Zwiggelaar and Boggis, 2001; Zhang and Tan, 2002; Varma and Zisserman, 2004; Picard et al., 1993; Nguyen et al., 2011) (http://vivid.cse.psu.edu/texturedb/gallery/albums.php?set_albumListPage=2). The Brodatz texture database is derived from the Brodatz album. The Brodatz textures are the most commonly used texture data set, especially in the computer vision and signal processing community. Because they are so commonly used by previous texture analysis/synthesis works, it is almost inevitable to include at least some of them in a texture synthesis paper (On Brodatz Texture, 2012). It has 112 classes, and a small number of examples for each class. The Brodatz album contains 112 images with size 512×512 and 256 gray values after digitizing, showing a variety of textures, both small and large grained, collected for artistic purposes (Carkacioglu, 2003). These digital images are not scans of the pages from the texture book. The images are scans of a set of glossy black and white prints that were purchased from the author. While these prints are pictures of the same textures as in the book, in most cases they are not the same image as the one in the book (Brodatz, 1966). Despite the popularity, however, Brodatz textures are actually copyrighted (On Brodatz Texture, 2012), even though many researchers are using these images.

The *Brodatz* texture database is based on image rotated textures. Various algorithms exploit the *Brodatz* texture database for evaluations, though in most of the cases, the entire database is not employed. Different papers use various number of image sets from this dataset. For example, 23 distinct natural textures are selected from the Brodatz album in (Laine and Fan, 1993). Some 209 natural texture images are used for training and 180 different texture images are used for testing by Hermes et al. (1999). They also use 48 synthetic texture images for classification (Hermes et al., 1999), along with all 112 Brodatz textures included in (Brodatz, 1966). Refs. Sayadi et al. (2008), Ong and Khoo (2009), Materka and Strzelecki (1998), Zhang and Tan (2002), Rajpoot and Rajpoot (2004) use Brodatz database (Brodatz, 1966) too. Ref. Sayadi et al. (2008) exploit only 25 Brodatz textures from the Brodatz dataset. Ref. Ojala and Pietikäinen (1998) use 15 textures only. Only a few publications actually report results on the entire database (Lazebnik et al., 2005; Picard et al., 1993; Georgescu et al., 2003; Liu and Picard, 1996; Xu et al., 2000) and most others use a partial set of textures. Fig. 1(a) shows some sample frames from this database.

Brodatz texture set is indispensible, even with the existence of VisTex (Otsuka et al., 1998; Liu et al., 2004a). The reason is that most of the Brodatz textures are photographed under controlled lighting conditions, so the images are of very high quality. In addition, they expose to the most amount of textures so that irrelevant information such as noise and 'non-textural' stuff are not there (On Brodatz Texture, 2012). One key concern of this texture database is that it cannot provide photometric stereo image sets for each texture class. This dataset also cannot provide true surface rotation (Zhang and Tan, 2002). Moreover, in recent years, it has been criticized because of the lack of intra-class variation that it exhibits (Lazebnik et al., 2005). This dataset has relatively impressive diversity of textures, where some of which are quite perceptually similar, while others are so inhomogeneous that a human observer would arguably be unable to group their samples 'correctly' (Lazebnik et al., 2005). Due to the variety of the scales and geometric patterns of the Brodatz textures, as well as the lack of intra-class transformations, the dataset becomes a good platform for testing the discriminative power of an additional *local shape* channel in a context where affine invariance is not necessary (Lazebnik et al., 2005).

3.2. Vision Texture database (VisTex)

The Vision Texture Database (VisTex) is another well-known database (Singh and Sharma, 2011; Otsuka et al., 1998; Liu et al., 2004a; Massachusetts Institute of Technology, 2012; Carkacioglu, 2003), formed by the Vision and Modeling group at the MIT Media Lab. It contains 167 colored reference textured images with size either a 786×512 or 512×786 image depending on the orientation of the scene (also have other sizes). Images are grouped according to their contents. Unlike other texture collections, the images in VisTex do not conform to rigid frontal plane perspectives and studio lighting conditions. The goal of VisTex is to provide texture images that are representative of real world conditions. The VisTex database can serve as a replacement for traditional texture collections (Massachusetts Institute of Technology). Moreover, the VisTex also provides some examples of many non-traditional textures (such as texture scenes and sequences of temporal textures). The experimental setup of Rajpoot and Rajpoot (2004) consists of images from the Brodatz and MIT VisTeX (Kassner and Thornhill, 2010) texture databases and a combination of some images therein. Two image sets are currently available covering homogeneous textures and multi-texture scenes (http://www.texturesynthesis.com/meastex/www/for_images.html). Both sets are distributed as raw PPM files with annotations declaring image content, lighting conditions, and perspective. The homogeneous textures (called Reference Textures) are distributed as both 128×128 pixel and 512×512 pixel images and the multi-texture scenes are distributed as both 192×128 pixel and 786×512 pixel images (http://www.texturesynthesis.com/meastex/www/for_images.html). Fig. 1(b) depicts few images for this dataset.

The most difference between the VisTex database and other texture databases is that it does not conform to *rigid frontal plane perspectives* and *studio lighting conditions*. For this dataset, the lighting conditions are daylight, artificial-florescent and artificial-incandescent, and some of the lighting conditions are imprecise. For example, descriptions are given as *'daylight, direct and from right'*. VisTex textures are photographed under natural lighting conditions, so they are tougher; i.e., the images contain more noise, and extra visual cues such as shadows, lighting, depth, perspective, etc. (On Brodatz Texture, 2012). With regard to perspective, the angle between films an object plane, there are two settings: frontal-plain and oblique. Therefore, considering the limitations of the VisTex database with unknown illumination directions, one may not use them with texture classification scheme, where one has to recover the surface properties from several images with the known

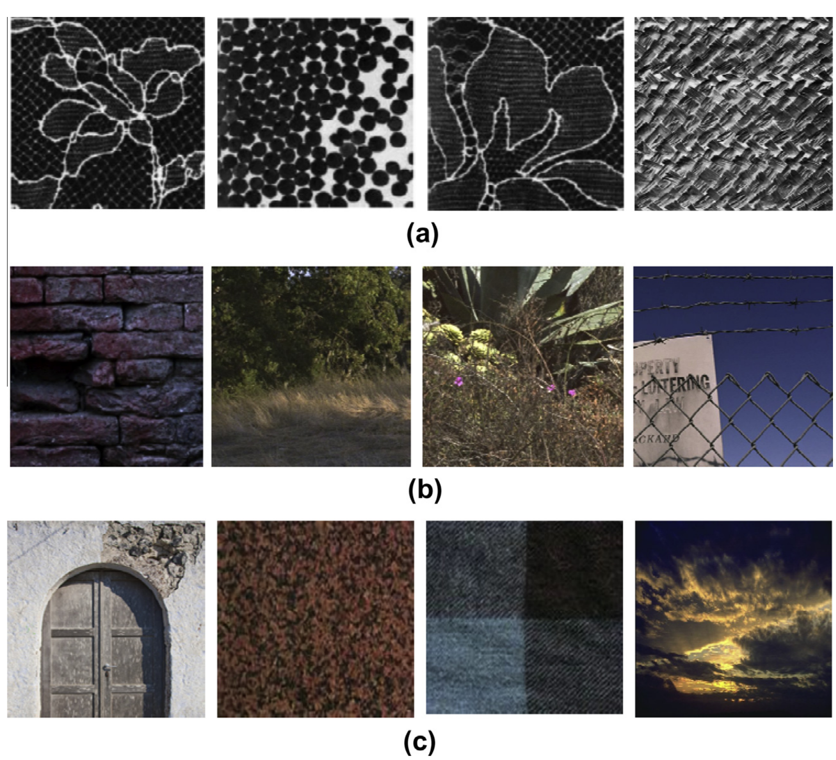

Fig. 1. Natural texture image dataset: Four sample images of (a) Brodatz texture set (Brodatz, 1966); (b) VisTex dataset (Otsuka et al., 1998; Liu et al., 2004); (c) Texture library dataset (http://textures.forrest.cz/).

and controlled light conditions using photometric stereo. In future, they want to include video textures and video orbits (Massachusetts Institute of Technology).

3.3. USC–SIPI texture mosaic

The USC–SIPI (University of Southern California–Signal and Image Processing Institute) Texture Mosaics dataset has three Texture Mosaic images (Weber, 2004) that are available on the USC–SIPI website (USC–SIPI database, 2012). Texture Mosaic#1 (Laws, 1980) has image of 512 × 512 pixel, containing eight textures in square regions of 128 × 128, 32 × 32, and 16 × 16 pixels. Mosaic#2 is created to provide a test image similar to mosaic#1 but with information about the contents of the image. It is composed of eight different texture samples (i.e., grass, water, sand, wool, pigskin, leather, raffia, and wood) taken from the Brodatz texture book (Brodatz, 1966). All eight textures are present in the image in squares of size 128 × 128, 64 × 64, 32 × 32, and 16 × 16. And the mosaic#3 is developed to test the effect of non-horizontal and non-vertical texture boundaries. It also contains the same eight Brodatz textures that are present in the first mosaic. The textures are present in the image in approximately equal proportions. The mosaic consists of three basic regions (Weber, 2004): the upper-left portion contains three textures in an arrangement where two textures are converging along curved paths; the upper-right portion of the new mosaic contains regions with non-vertical and non-horizontal boundaries, both straight and slightly curved. The bottom half of the image is made up of the eight textures in irregularly shaped regions of approximately equal size (Weber, 2004).

There is another dataset under the same group, called the USC–SIPI (University of Southern California–Signal and Image Processing Institute) 'Rotated Textures', which is part of the textures volume consist of thirteen of the Brodatz texture images each digitized at seven different rotation angles: 0°, 30°, 60°, 90°, 120°, 150°, and 200° (total of 91 images)) (USC–SIPI database, 2012). The images are all 512 × 512 pixels with 8 bits/pixel. These rotated texture images are scanned using a 512 × 512 pixel video digitizing camera. Hence, the quality of the scanned images are probably not as good as those in the main part images.

3.4. Texture library

This is a library of various textures from different types of images (http://textures.forrest.cz/). It has 17 albums of various high resolution images on doors, forest, bump, cloud, fabric, maps, nature, etc. Though it has a good variability in terms of different classes as well as resolutions, no published report has been found on its usage. Also, Textile Texture Database (TILDA) and Forrest Texture library have various images from forests, e.g., trees, bark, moss, rock, etc. in high resolution. Fig. 1(c) shows some image frames.

4. Texture of materials

This section presents most of the texture datasets available in the literature. Most of the datasets are based on various real-life materials, though partially these cover natural textures and scenes as well. Measurement of Texture (MeasTex) database has both natural as well as artificial texture images. We split these datasets under this group considering the types of images and/or applications. These texture datasets are suitable to analyze materials, surfaces, object recognition, pattern analysis, etc. A good number of these are Photometric Texture databases. We will notice more distinct features in Discussions and Tables presented below.

4.1. Meastex (MEASurement of TEXture) database

The MEASurement of TEXture (Meastex) sets contain examples of artificial and natural texture images (Sharma et al., 2001). The term 'natural' here is used to mean textures, which occur in the real world (http://www.texturesynthesis.com/meastex/www/for_images.html). The natural images have been chosen for their homogeneity of texture. Each image has a size of 512 × 512 pixels and is distributed in raw PGM format (http://www.texturesynthesis.com/meastex/www/for_images.html). Each image is split into 16 sub-images to increase the number of samples available for each class. The textures are of four classes: asphalt (64 images), concrete (192 images), grass (288 images) and rock (400 images), which provide total 944 images. The artificial textures are generated by the makeBrick program that creates brick-like textures (http://www.texturesynthesis.com/meastex/www/for_images.html). The program initially creates a stone texture background by randomly bombarding a blank image with Gaussian blobs. The blobs may be elongated and rotated (http://www.texturesynthesis.com/meastex/www/for_images.html). Brick textures may then be created by either overlaying the stone texture with a mortar pattern or transferring randomly cut bricks from the stone texture and placing in a new image, separating the bricks with mortar. There are three texture sets are available here, namely – bomb (normal background texture), lattice (overlaying normal background texture with mortar), and mortar (separating randomly cut bricks with mortar). On the other hand, some natural textures are compiled (and continued process) to create a database of natural textures. The images have been obtained from 6″ × 4″ color photographs taken with a 35 mm camera (http://www.texturesynthesis.com/meastex/www/for_images.html). Each photograph is scanned at 256 dpi and stored in PPM format. The distributed images are 512 × 512 pixels areas, which have been cropped from these full-size images and converted to PGM format. In this dataset, similar to the VisTex annotations, annotation header is used to label each image. For example, a comprehensive database of grasses (most labeled with species) makes up a large proportion of the textures in this set. Other significant texture sets are based on materials and surface textures. Ref. Ojala and Pietikäinen (1998) propose a multi-channel approach to texture description where they compare the Brodatz textures (15 textures only) and MeasTex datasets. Ref. Ojala and Pietikäinen (1999) explored this dataset as well. Singh and Sharma (2011) analyze texture on MeasTex benchmark.

Although a number of texture sets in MeasTex have been compiled by other texture databases such as the Brodatz texture database and the VisTex database, most of their natural textures are 2D texture rather than 3D texture. The MeasTex provides a database of homogeneous texture images, several test suites of texture classification problems, implementations of major texture classification paradigms, and a framework for the quantitative measurement of texture classification algorithms on the texture problem test suites (MeasTex). See Fig. 2(a) for few images for MeasTex dataset.

4.2. PhoTex (Photometric image set with a wider variation of illumination directions) database

Heriot-Watt University at Edinburgh creates Photometric Texture Database (PhoTex); Drbohlav and Chantler, 2005; Targhi et al., 2008; Carkacioglu, 2003 that consists of images of surface textures that are observed from a constant viewpoint for 40 different illumination directions. It is a texture database of rough surfaces, and a few smooth surfaces. The main variables in the database are azimuth and zenith of the illumination. In few cases, the surface sample is also rotated. This database therefore mainly focuses on the changes of illumination condition rather than the surface rotation. This database is intended to provide

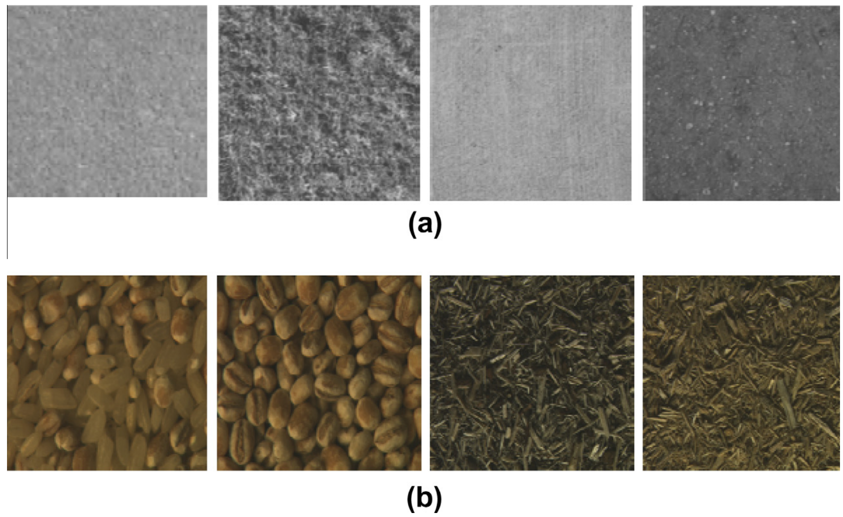

Fig. 2. Four bodies of (a) Meastex dataset (Sharma et al., 2001); (b) OUTex dataset (Ojala et al., 2002).

physics-based, photometric data for texture research. It is called this database as physics-based (which means it is applied to algorithms that model, or account for, the physical process of image formation and capture) because image surfaces are taken under controlled conditions, and calibration images are taken that enable the imaging process to be modeled (PhoTex Database). Images that allow the user to calibrate the image transfer function, and measure the noise in the process are also held in the database.

The images are grayscale with resolution of 1280 × 1024 pixels. These are unprocessed TIFF images. Images are captured by using a Vosskuhler CCD 1300LN digital camera, with a Matrox PC-SIG framestore. The measured intensity in the images of this dataset is proportional to irradiance. This database seems important for texture researchers who are working on illuminant direction invariance, surface rotation invariance and photometric shape estimation. Another potential point is that researchers interested in extracting and processing information from rough surfaces can use this dataset.

4.3. PhoTex (Photometric image set with a wider variation of illumination directions) 3D database

The Photometric Texture (PhoTex) project has a recent target to develop a new methodology for texture classification based on the direct use of surface gradient (relief) and surface reflectance (albedo) information (PhoTex). This dataset provides real surface rotation rather than image rotation, where most of currently existing texture databases only support image rotation; and registered photometric stereo data sets, where 3D texture surfaces are captured under the controlled illumination conditions. This is the first texture database that provides both full real surface rotations and registered photometric stereo data, which is different from other existing texture database (PhoTex). It contains 30 real textures, and there are currently 1680 images in the database. This will enable the design of image texture analysis systems that exploit and take into account the illumination conditions and the three-dimensional nature of texture. The dataset can be available from Download: (http://www.taurusstudio.net/research/pmtexdb/download.htm).

4.4. Amsterdam Library of Textures (ALOT) database

Amsterdam Library of Textures (ALOT) database (Targhi et al., 2008; Chantler et al., 2005; Drbohlav and Chantler, 2005; Burghouts and Geusebroek, 2009; Vácha et al., 2011) (http://www.science.uva.nl/_mark/ALOT) consists of 250 rough texture classes (100 number of images per class), which systematically varied the viewing angle and illumination angle so that it can capture the sensory variation in texture recordings. It has eight different illuminations in three orientations, having four viewpoints. These are divided into tune, train, and test parts, each with 2400 samples. Fig. 3 shows some textures from the ALOT dataset. The ALOT dataset includes some very easily recognizable materials as well as extremely difficult ones. Although the number of view-illumination directions per material is only half the BRDF bi-directional reflectance distribution function) resolution of Columbia-Utrecht Reflectance and Texture (CUReT) database, the ALOT extents the number of materials almost by a factor 5, and it improves upon image resolution and color quality. Furthermore, different light source colors have been added to test (texture) color constancy algorithms. The acquisition setup for the ALOT is very similar to the ALOI collection of objects (Targhi et al., 2008).

Note that due to small misalignments between the two cameras, the viewpoints are not perfectly (pixel accuracy) identical (Targhi et al., 2008). For materials with not too much depth variation, the distortion can be well approximated by a planar rotation and translation between the two views. Hence, image homography registration can be applied to align the images between the two cameras (Targhi et al., 2008).

4.5. UMD dataset

The UMD (University of Maryland, College Park) is a dataset of high-resolution texture (Xu et al., 2006a,b, 2009a,b, 2010) (http://www.cfar.umd.edu/~fer/High-resolution-data-base/hr_database.htm) that consists of 1000 un-calibrated, unregistered images, taken from a family camera. It has 25 texture classes with 40 samples, having resolution of 1280 × 900 pixels. Similar to the UIUC Database, within each class – the UMD texture dataset has significant viewpoint changes and scale differences. Moreover, the illumination conditions are uncontrolled for the UMD dataset. The textures of this dataset are non-traditional, including images of fruits, various plants, floor textures, shelves of bottles and buckets (Xu et al., 2006b). The dataset can be available upon request to the authors, as mentioned in Ref. Xu et al. (2006b). Fig. 4(a) shows a sample texture image per class.

4.6. OUTex database

The OUTex database (Ojala et al., 2002; Burghouts and Geusebroek, 2009; Corani et al., 2010; Shi and Manduchi, 2005) (http://

Fig. 3. Some sample images from the Amsterdam ALOT database (ALOT class numbers are shown in ()); Row#1: tea-wafers (9), brown bread (26), cotton (43), terry cloth (48), punched plastic (56); Row#2: cork (57), cotton (60), ribbed cotton (64), sponge (176), chamois (196) (Targhi et al., 2008) (http://www.science.uva.nl/_mark/ALOT).

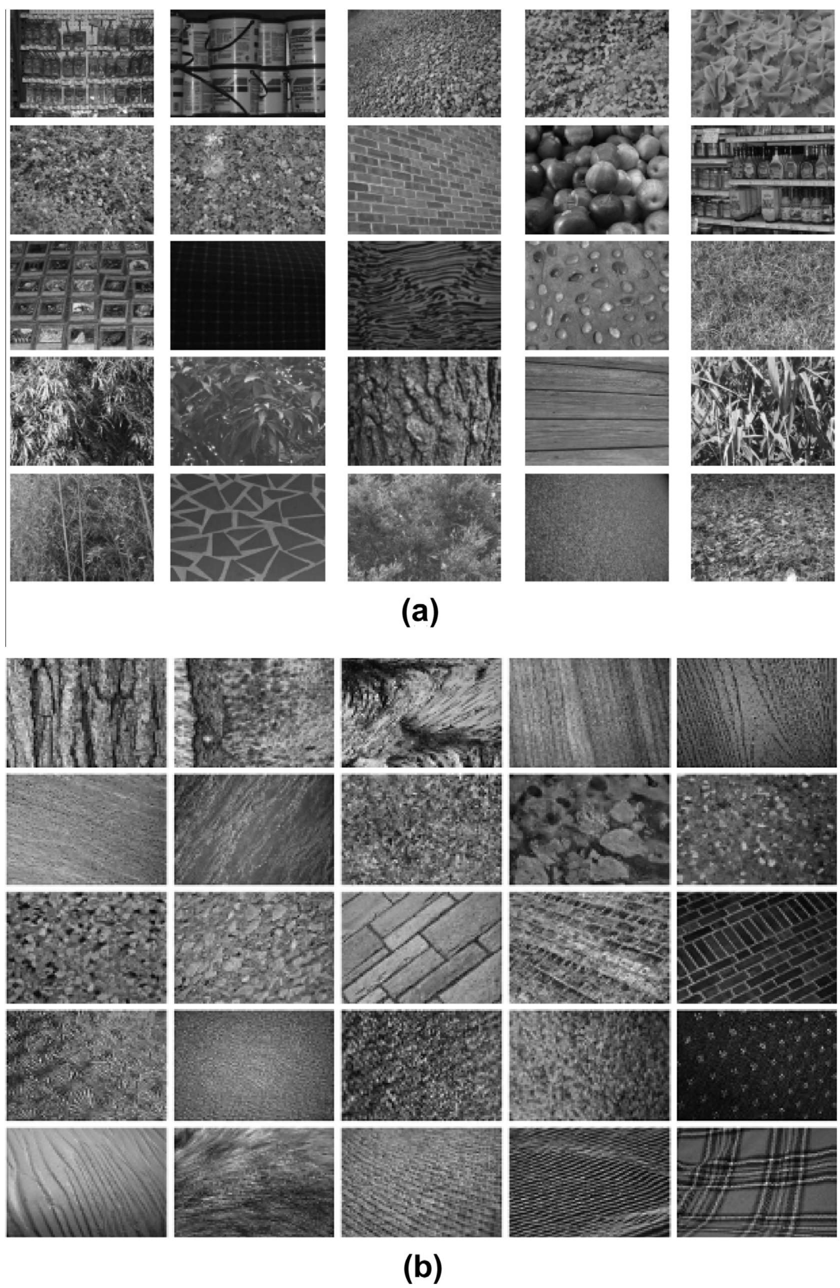

Fig. 4. Example of 25 classes each from: (a) UMD dataset (Xu et al., 2006b); (b) UIUC database (Varma and Ray, 2007).

www.outex.oulu.fi/) stands for University of Oulu Texture database. This image database contains a large collection of textures, both in the form of surface textures and natural scenes. The OUTex is a framework for empirical evaluation of texture classification and segmentation algorithms. The surface textures have wide variations in terms of illumination direction (three illumination sources), surface rotation, and spatial resolution. Note that the OUTex database cannot be used to provide registered photometric stereo data (Photometric Texture Database). In this case, all three different illumination directions are lying on the same plane – either coplanar or collinear. And these illumination variations vary only in the change of slant angle, while the tilt angle remains constant. Hence, it is not possible to correctly resolve the surface partial derivatives from these images using photometric stereo, as the inverse of the lighting matrix in the photometric stereo solution does not exist when the three illumination vectors lie in the same plane (Photometric Texture Database). Fig. 2(b) shows some images for OUTex dataset.

4.7. Columbia-Utrecht Reflectance and Texture database (CUReT)

The Columbia-Utrecht Reflectance and Texture (CUReT) database is another well-known and very challenging database (Dana et al., 1999; Dana and Nayar, 1999; Lazebnik et al., 2005; Zhang et al., 2006, 2007; Varma and Zisserman, 2002, 2003, 2004, 2005; Broadhurst, 2005; Leung and Malik, 2001; Cula and Dana, 2001, 2004; Geusebroek and Smeulders, 2005; Pietikainen et al., 2004; Caputo et al., 2005; Vácha et al., 2011; Crosier and Griffin, 2008; Xie and Mirmehdi, 2005; Burghouts and Geusebroek, 2006). The CUReT database is a considerable improvement over the Brodatz collection. The CUReT is developed at Columbia University and Utrecht University. This is a variety of tile datasets with different types of defects including physical damage, pin holes, textural imperfections, pattern mis-registrations, etc. The test samples have resolution of 512×512 pixels. It has 61 different materials. It has many real world textures, taken under varying image conditions, and the effects of specularities, shadowing and other surface normal variations are evident (Varma and Zisserman, 2005). The set of images for each texture sample is obtained over a wide range of viewing and illumination directions. Fig. 5 shows three images for the same materials in different illuminations and poses. Various material images from the Columbia-Utrecht database (CUReT) are exploited by Xie and Mirmehdi (2005).

Though the CUReT database is a good one, it has some constraints too. For example, there is no significant scale change for most of the textures and limited in-plane rotation. In this case, for all measurements of a selected texture sample, the light source remains fixed. It is noted that a camera is mounted on a tripod and its optical axis is parallel to the floor. Therefore, it can be positioned to any one of seven different locations in a plane during measurements. For each camera position and a given light source direction, the texture sample is rotated, however, without significant variation in scale or in-plane rotation (Crosier and Griffin, 2008).

The images in the database do not exhibit significant scale variation, hence, scale-invariant features tend to perform worse than features with just rotation or even no invariance but higher discriminative power (Crosier and Griffin, 2008). The images are not suitable to sparse interest point-based methods. Apart from this, it is noticeable that multiple instances of the same texture are present for only a very few of the materials, so intra-class variation cannot be investigated; and therefore, it is difficult to make generalizations (Varma and Zisserman, 2005). The standard methodology on the CUReT database is to report results for 92 images per class (Crosier and Griffin, 2008). Some images of this dataset do not have a sufficiently large portion of the texture visible to be cropped from the background. The measurement setup for CUReT database is not suitable for photometric stereo, as for a given texture sample at a certain orientation, it is necessary to capture the different images by fixing the position of camera and moving the light source, not by fixing the light source and moving camera.

The CUReT has three texture databases, namely –

(i) BRDF (bi-directional reflectance distribution function) database;
(ii) BRDF parameter database; and
(iii) BTF (bi-directional texture function) database.

(i) BRDF (bi-directional reflectance distribution function) database: The BRDF database has 61 different samples for reflectance measurements. Each of these samples is observed with over 205 different combinations of viewing and illumination directions. Dana and Wang (2004) presented a new bidirectional imaging device or texture camera that allows convenient measurements of a spatially varying BRDF.

(ii) BRDF parameter database: The BRDF parameter database with fitting parameters from two recent BRDF models (Oren–Nayar reflectance model (Oren and Nayar, 1994a,b) for surfaces with isotropic roughness; and the Bidirectional reflection distribution function (Koenderink et al., 1996) for both anisotropic and isotropic surfaces) are developed. These BRDF parameters can be directly used for both image analysis and image synthesis.

(iii) BTF database: Similar to the BRDF database, the BTF (bi-directional texture function) database also has 61 real-world surfaces that are measured by using new texture representation called BTF. A good survey on BTF is done by Filip and Haindl (2009).

The CUReT database combines the foreshortening effect of the texture and the associated changes in its corresponding illumination directions. The availability of the CUReT offers rare but important databases to analyze the BRDF and BTF of textures. Muller et al. (2005), Neubeck et al., (2005), Cula et al. (2004), Furukawa et al. (2002), Ngan and Drand (2006), Sattler et al. (2003) also work with BTF data (e.g., Bonn University BTF Database, 2003) for their experiments.

Koudelka et al. (2003) develop a new BRDF texture dataset that contains about 10,000 color, 480x360 images, about 50 times the number of images for a single sample in the CUReT database.

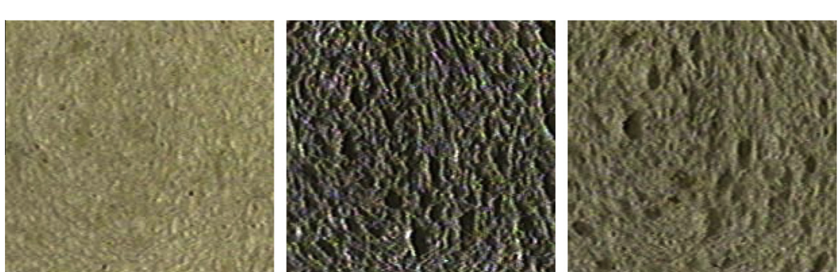

Fig. 5. Example of CUReT database: 'white-bread' image in three different poses and illuminations (Hayman et al., 2004).

4.8. Textile database

Another database is developed to detect defects in the textile products (Aras et al., 1999; Ozdemir et al., 1998). These are gray-level images of dimension 256×256, taken by a Sony CCD Iris SSC-M370CE camera in a laboratory environment. While acquisition of this database, frontal lighting system is employed, where the camera and the light source are placed on the same side of the fabrics. Each image corresponds to $8.53 \text{ cm} \times 8.53 \text{ cm}$ fabric with a resolution of 3.33 pixels/mm, which is the same resolution that is required in the factory environment. In (Aras et al., 1999; Ozdemir et al., 1998), the texture image sample set on which the experiments are performed contains images of eight different texture types. The first texture type has 35 images: 19 of them contain defects and the rest are defect-free or clean. Remaining seven sets of texture types contain four images per type, where two are defected and two are defect-free. The defects are considered according to the common defects.

4.9. UIUC database

The UIUC database (Lazebnik et al., 2005; Hayman et al., 2004; Zhang et al., 2006, 2007; Varma and Zisserman, 2003; Xu et al., 2009a,b, 2010; Crosier and Griffin, 2008; Varma and Garg, 2007; Nguyen et al., 2011) contains 40 images each of 25 different texture classes, hence total 1000 un-calibrated, unregistered images. These are gray-scale images having image resolution 640×480 pixels. It is available publicly in (UIUC Database). The database includes surfaces whose texture is due mainly to albedo variations (e.g., wood and marble), 3D shape (e.g., gravel and fur), as well as a mixture of both (e.g., carpet and brick) (Lazebnik et al., 2005). Moreover, within each class, viewpoint changes and scale differences are strongly evident. Illumination conditions are uncontrolled too for this database (Lazebnik et al., 2005; Crosier and Griffin, 2008). The database contains materials imaged under significant viewpoint variations and also contains fabrics which display folds and have non-rigid surface deformations (Varma and Ray, 2007). Fig. 4(b) shows some images for 25 classes.

It has significant changes in scale and viewpoint as well as non-rigid deformations; although with less severe lighting variations than CUReT (Crosier and Griffin, 2008). Some additional variability issues are also considered, e.g., non-planarity of the textured surface (bark), significant non-rigid deformations between different samples of the same class (e.g., fur, fabric, and water), inhomogeneities of the texture pattern (e.g., bark, wood, and marble), and viewpoint-dependent appearance variations (e.g., glass) (Lazebnik et al., 2005). The dataset has relatively few sample images per class but high intra-class variability, including non-homogeneous textures and unconstrained non-rigid deformations (Lazebnik et al., 2005).

In terms of intra-class variations in appearance, this is the most challenging of the commonly used testbeds for texture classification (Crosier and Griffin, 2008). Though the UIUC database demonstrates improvement over the CUReT textures in terms of the former's significant viewpoint variations and having some considerable surface deformations, it is much smaller than the CUReT database, both in the number of classes as well as the number of images per class (Varma and Garg, 2007). Apart from this shortcoming, the UIUC database has very few instances of a given material so that it is difficult to perform categorization or deduce generalization properties of features (Varma and Garg, 2007). The high resolution of the images makes it unclear how features will perform in real-world settings where textured regions on objects might be much smaller (Varma and Garg, 2007). In terms of scale and other viewpoint variations are concerned, the UIUC database is by far the most challenging database (Varma and Garg, 2007). For example, the CUReT images have no scale variation (all materials are held at the same distance from the camera, only the orientation is changed), limited in-plane rotation, and the same physical surface patch is represented in all samples. Moreover, the appearance of each patch in that database is systematically sampled under different combinations of viewing angles and lighting directions, making it straightforward to select a fixed representative subset of samples for training, as is done in most CUReT evaluations (Lazebnik et al., 2005). Some methods (Varma and Garg, 2007; Lazebnik et al., 2005; Xu et al., 2006; Zhang et al., 2006) show comparatively better results on real world datasets, e.g., UIUC dataset (Lazebnik et al., 2005) and CUReT databases (Dana et al., 1999).

4.10. CMU Near-Regular Texture (NRT) database

The CMU Near-Regular Texture (NRT) database (Lazebnik et al., 2005; Liu et al., 2004a,b) is a difficult database and it covers the spectrum of textures from completely regular to near-regular to irregular (Liu et al., 2004a). It also includes video of near-regular textures in motion. This database also includes test image sets with ground truth for translation, rotation, reflection/glide-reflection symmetry detection algorithms. There is 15 top-level albums (89 total), covering 5775 images.

4.11. Rutgers skin texture database

The Rutgers Skin Texture Database is a dermatology bidirectional texture function (BTF) database (Cula et al., 2004). It has various skin diseases taken from the illumination and camera-controlled positions, containing bidirectional measurements of normal skin and of skin affected by various disorders. It has two combinations of viewing angles and illuminations: (i) four viewing and eight illumination positions; and (ii) three viewing and ten illuminations positions. Regarding measurement setup, this database has two different measurement setups, namely – (i) quartz halogen or fiber optic illuminator-based light arc; and (ii) camera mounted on a manually articulated arm on a tripod. They use a Sony DFW-V500 IEEE-1394 digital camera equipped with Infini-Mini video lens with variable focus. The complete database contains more than 3500 images, and is made publicly available. The database has two components:

(i) A normal skin component for recognition and rendering in computer vision and graphics. It has more than 2400 texture images of normal facial skin corresponding to 20 human faces, 4 locations on the face (forehead, cheek, chin and nose) and 32 combinations of imaging angles for each imaged surface (four camera poses, and eight light directions for each camera pose). The images in the database are acquired from both female and male subjects (7 females and 13 males), while the subjects age ranges from 24 to 53.

(ii) A skin disorder component for quantitative imaging in dermatology. It has 75 clinical cases, which include conditions like acne, rosacea, psoriasis, sebhorreic keratosis, dermatomyositis, actinic keratosis, congenital melanocytic nevus, keratosis pilaris, and dermatofibroma. Each case may correspond to a different patient and a different body location. Depending on the location of the disorder, there are images from the face, arms, legs, back and abdomen. Each case has been measured with multiple texture images, and each image is characterized by a certain combination of imaging conditions.

4.12. KTH-TIPS (Textures under varying Illumination, Pose and Scale) database

The KTH-TIPS database (Lazebnik et al., 2005; Hayman et al., 2004; Zhang et al., 2006, 2007; Varma and Zisserman, 2003; Targhi et al., 2008; Burghouts and Geusebroek, 2009; Crosier and Griffin, 2008; Nguyen et al., 2011) expands CUReT database by photographing new samples of ten of the CUReT textures at a subset of the viewing and lighting angles used in CUReT but also over a range of scales. Each class contains 81 images. Texture samples are 200×200 images except some sample of two classes (i.e., cracker and brown-bread). Images of the materials present in the KTH-TIPS database (which are also present in the CUReT database) are sandpaper, crumpled aluminum foil, styrofoam, sponge, corduroy, linen, cotton, brown bread, orange peel and cracker B. These are imaged at nine distances from the camera to give equidistant log-scales over two octaves (Hayman et al., 2004). At every direction, images are captured using three directions of illumination (i.e., front, side and top) and 3 poses (i.e., central, 22.5° turned left, 22.5° turned right), which provides a total of $3 \times 3 = 9$ images per scale, and $9 \times 9 = 81$ images per material (Hayman et al., 2004). It was created to extend the CUReT database in two directions: (i) by providing variations in scale as well as object poses and illumination directions, and (ii) by imaging other samples of a subset of its materials in different settings. Fig. 6(a) shows some example frames of KTH-TIPS database.

Since the CUReT database contains little scale variation, this dataset is introduced which images ten CUReT materials at different distances, while also maintaining some change in pose and illumination (Hayman et al., 2004). As mentioned above, one of the key objectives of this database is to attempt to recognize 'different samples' of the CUReT materials. It is *not* possible to do recognize different samples with any acceptable degree of accuracy (Hayman et al., 2004).

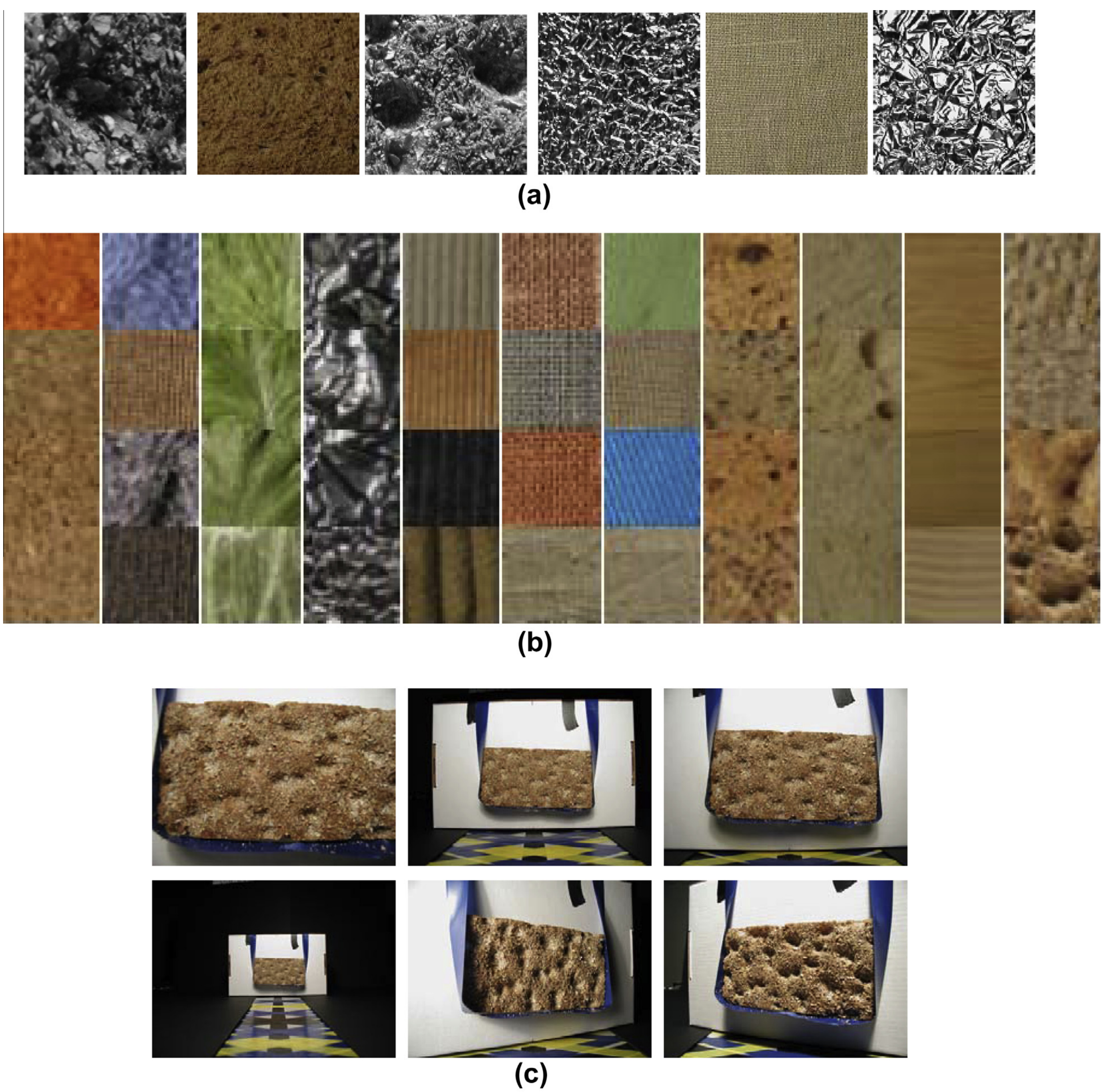

Fig. 6. Some sample images from: (a) KTH-TIPS dataset (Lazebnik et al., 2005; Hayman et al., 2004); (b) KTH-TIPS2 material database (each column represents (sequentially) cork, wool, lettuce leaf, aluminum foil, corduroy, linen, cotton, brown bread, white bread, wood and cracker; (c) An example that depicts the KTH-TIPS dataset's variations in terms of scale, pose and illumination (Hayman et al., 2004).

4.13. KTH-TIPS2 material database

The KTH-TIPS2 material database (Hayman et al., 2004; Mallikarjuna et al., 2006; Caputo et al., 2005) is built on the KTH-TIPS database and provides a considerable extension by imaging *multiple* different samples of different materials. Many of these materials have 3D structures, implying that their appearance can change considerably as pose and lighting are changed. It has all types of images of the KTH-TIPS, in addition to 'lettuce leaf' image. Fig. 6(b) shows some images for this dataset. The database contains images at 9 scales, equally spaced logarithmically over two octaves. It has 3 poses and 4 illumination conditions (frontal, 45° from the top and 45° from the side, all taken with a desk-lamp with a Tungsten light bulb) (e.g., Fig. 6(c)), and for the fourth illumination condition fluorescent lights in the laboratory are considered. Although some variation in pose and illumination is present, both KTH-TIPS and KTH-TIPS2 contain significantly fewer settings for lighting and viewing angle than CUReT (Caputo et al., 2005).

4.14. PerTex database

PerTex database is developed by Fraser Halley (Varma and Ray, 2007). The PerTex database has 334 photometric height maps with perceptual similarity matrix.

4.15. Building texture database

The Building Texture Database (http://www.photomichaelwolf.com/hongkongarchitecture/) has blocks, finding a mesmerizing abstraction in the buildings' facades. Some of the structures in the series are photographed without reference to the context of sky or ground, and many buildings are seen in a state of repair or construction.

4.16. Grain mixtures dataset

The grain mixtures dataset (Kjell, 1992; Ojala et al., 1996) use images of eleven different mixtures of rice and barley grain. Image resolution is 128×128 pixels. Both of these were rather similar in size, rice was a little more elongated than barley and barley had a wider range of gray levels than rice.

4.17. Kylberg texture dataset

The Kylberg texture dataset (Kylberg, 2011) (http://www.cb.uu.se/~gustaf/texture/) has a number of textured surfaces, including fabrics and surfaces of stone, were imaged in the local surroundings. Textured surfaces were also arranged using articles such as rice grains, sesame seeds and lentils.

5. Dynamic texture database

The above-mentioned databases are based on static images. However, there are some new types of datasets called dynamic texture dataset where the temporal textures are variable and changing temporally. Now what is the meaning of 'dynamic texture'? it is known that for a single image, a texture can be defined as a realization from a stationary stochastic process with spatially invariant statistics (Zhu et al., 1997), which portrays the intuitive notion of texture. For a sequence of images (i.e., time-varying texture), individual images are clearly not independent realizations from a stationary distribution, for there is a temporal coherence intrinsic in the process that needs to be captured. The underlying assumption, therefore, is that individual images are realizations of the output of a dynamical system driven by an independent and identically distributed (IID) process. Dynamic textures are sequences of images that exhibit some form of temporal regularity (Doretto and Soatto, 2003). According to Yuan et al. (2004), dynamic texture can be defined as a temporally continuous and infinitely varying stream of images that exhibit certain temporal statistics. In another term, dynamic textures are video sequences of images of moving/non-rigid scenes that exhibit certain stationary properties in time; these include sea-waves, smoke, foliage, whirlwind, etc. (Doretto et al., 2003a,b). Another definition of the term dynamic texture is usually used with reference to image sequences of various natural processes that exhibit stochastic dynamics (Culibrk et al., 2012).

There are some dynamic texture databases (Peteri and Chetverikov, 2004), which are more difficult to analyze. Dynamic texture analysis and synthesis have recently become an active research topic in computer vision and computer graphics (Yuan et al., 2004). Similar to 2D texture synthesis, the goal of dynamic texture synthesis is to generate a new sequence that is similar to, but somewhat different from, the original video sequence (Yuan et al., 2004). A number of recent works have concentrated on dynamic textures and their evaluations, segmentation, synthesis, and recognition (Otsuka et al., 1998; Peh and Cheong, 2002; Saisan et al., 2001; Chan and Vasconcelos, 2007; Dana and Nayar, 1999; Peteri and Huskies, 2005; Szummer, 1995; Peteri and Chetverikov, 2005; Woolfe and Fitzgibbon, 2006; Szummer and Picard, 1996; Chan and Vasconcelos, 2006; Fazekas and Chetverikov, 2005; Ghanem and Ahuja, 2010a,b; Zhao and Pietikainen, 2006; Ravichandran et al., 2009; Doretto and Soatto, 2002, 2003; Doretto et al., 2003a,b; Chan and Vasconcelos, 2005; Cooper et al., 2005; Vidal and Ravichandran, 2005; Yuan et al., 2004; Schodl et al., 2000; Peteri et al., 2010; DynTex; Culibrk et al., 2012). The following sub-sections present the benchmark datasets for dynamic or temporal texture databases.

5.1. UCLA dynamic texture database

The UCLA dynamic texture database (Saisan et al., 2001; Dana and Nayar, 1999; Woolfe and Fitzgibbon, 2006; Chan and Vasconcelos, 2006; Ghanem and Ahuja, 2010b; Doretto and Soatto, 2002, 2003) contains 50 classes of various dynamic texture video textures, including boiling water, fountains, fire, waterfalls, rippling water, and plants and flowers swaying in the wind. Each class contains four gray-scale sequences with 75 frames of 160×110 pixels. Each sequence was clipped to a 48×48 window that contained the representative motion. For each scene, all four example sequences are captured with the same viewing parameters (e.g., identical viewpoint). In total there are 200 sequences. Ref. Ghanem and Ahuja (2010a) obtains the recognition results of 95.6% for this database, whereas Ref. Saisan et al. (2001) achieves 97.5% accurate classification rate. The UCLA dataset is currently the benchmark for dynamic texture recognition, even though a much larger and more diverse database (the DynTex database (Peteri and Huskies, 2005; Peteri et al., 2010) exists (Ghanem and Ahuja, 2010a). The UCLA dataset remains the benchmark due to the following properties (Ghanem and Ahuja, 2010a):

(i) Its dynamic texture sequences have already been pre-processed from their raw form, whereby each sequence is cropped to show its representative dynamics in absence of any static or dynamic background.
(ii) Only a single dynamic texture is present in each dynamic texture sequence.
(iii) In each dynamic texture sequence, no panning or zooming is performed.
(iv) Ground truth labels of the dynamic texture sequences are provided.

5.2. UCLA Pan-database

A second database containing panning video textures is produced from the original UCLA video textures (Chan and Vasconcelos, 2007). Each video texture is generated by panning a 40×40 window across the original UCLA video. In this case, four pans (two left and two right) are generated for each video sequence, resulting in a database of 800 panning textures, which is called the UCLA-pan database (Chan and Vasconcelos, 2007). The motion in this database is composed of both video textures and camera panning, hence the dynamic texture is not expected to perform well on it. Details of these UCLA dynamic texture databases are available in (Chan and Vasconcelos, 2007).

5.3. DynTex database

The European FP6 Network of Excellence MUSCLE develops a dynamic texture database called DynTex (Peteri and Huskies, 2005; Peteri et al., 2010; DynTex; Culibrk et al., 2012). The DynTex dataset contains more than 650 varied dynamic texture videos, but the information about the type of textures shown in the sequences is not provided for all the videos in the set. The image size is 352×288 and the compressed videos provided are coded using DivX codec. A subset of 202 sequences, spanning some 23 classes of very varied dynamic textures has been selected to evaluate the method of Culibrk et al. (2012). Some of the DynTex sequences, such as mixtures of essentially different processes, are obviously inhomogeneous and non-stationary. Examples of some texture classes of this database are – textile, vegetation, grass, NA, streaks, water, steam, fire, smoke, branch, cloud, leaf, car, needle, fur, tentacle, insects, CD, foam, light and paper.

Central to the database is the so-called golden set of high-quality dynamic texture sequences that satisfy all criteria of the acquisition protocol (DynTex). This set can be further structured by its underlying physical processes, e.g., turbulent motion, waving motion, discrete units, etc. Additionally, they will be classified by their shot type, i.e., either as closeup (shot consisting entirely of the dynamic texture, no segmentation required), or as context (the dynamic texture is shown in its context) (DynTex). Next to the golden set we will offer various other sets. Examples are a collection of dynamic texture sequences recorded with a moving camera, and a collection with several dynamic textures per sequence (DynTex). However, the DynTex database lacks the four key properties of UCLA dynamic texture database. It is exploited by various researchers, e.g. (Ghanem and Ahuja, 2010a; Zhao and Pietikainen, 2006; Fazekas and Chetverikov, 2005). More details on this dataset are available in (DynTex). Fig. 7(a) shows five frames for five sequences of this dataset, namely tree sequence, river sequence, grass and river sequence, wave sequence, and field sequence.

5.4. Dynamic texture database

The dynamic texture database is developed by Saisan et al. (2001). It has a total of more than 250 sequences, consisting of moving scenes of smoke, boiling, fire, flowers, sea, water, fountain and waterfall. Each sequence is 150 frames long and pixels. Each sequence can be divided into two sub-sequences of 75 frames for a total of more than 500 sequences. Included in the database are similar sequences with different dynamics. For example, it has water stream, recorded from different angles, thus moving at different orientations and speeds. The database includes 76 different kinds of dynamic textures. Each of them is represented by eight distinct instances. Each sub-sequence consists of 75 frames. All frames are in color where the size of an individual frame is 220×320 pixels. It is used by Saisan et al. (2001), Chan and Vasconcelos (2007), Ravichandran et al. (2009), Ghanem and Ahuja (2010a). Ref. Chan and Vasconcelos (2007) achieved recognition results with this dataset as 97:5% by using the kernel version of the dynamic texture model and 96:5% by using just the Martin distance on the LDS parameters. Ref. (Ravichandran et al., 2009) achieved 100% recognition results for eight classes of this database. Note that the fountain and waterfall classes are the most difficult to classify because there are no clear appearance differences.

5.5. DynTex++ database

The UCLA benchmark dynamic texture dataset lacks much variety along the three DT dimensions, and therefore, (Ghanem and Ahuja, 2010a) proposed a new dynamic texture dataset, called DynTex++. The goal here is to organize the raw data in the DynTex

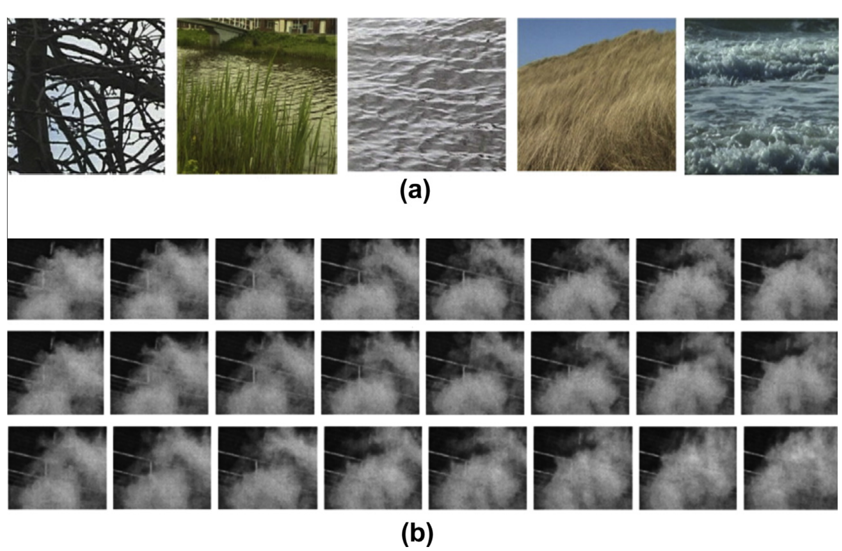

Fig. 7. (a) DynTex database – few sample frames (sequentially – tree sequence, river sequence, grass and river sequence, wave sequence, and field sequence) (Peteri and Huskies, 2005; Peteri et al., 2010); (b) MIT temporal texture database – few frames from 'smoke' (Szummer. Temporal Texture Modeling. Technical Report 346, 1995; Doretto et al., 2003a,b).

Table 1
Various properties of important texture databases.

Database	Image size	No. of class or images	Gray-level or color	Image rotation	Surface rotation
Brodatz	512 × 512	112 classes	Gray-level	Yes	Yes
Columbia-Utrecht Reflectance and Texture (CUReT)	512 × 512 or, 200 × 200	10 classes, usually 92 images per class		Yes – multi-view	Limited in-plane rotation
Vision Texture (VisTex)	786 × 512 or 512 × 786	167 images	Color	Yes	No
MEASurement of TEXture (MeasTex)	512 × 512; also in raw PGM format	4 classes, total 944 images		Yes	No
Photometric Texture (PhoTex)	1280 × 1024		In various formats and in SCOPE format	Constant view-p	No
OUTex	516 × 716	319 textures, 162 images per texture	Color and gray-level images	Yes, 6 different resolutions	9 rotation angles
MRI Brain					
Digital Database for Screening Mammography (DDSM)	3000 × 4500	Approximately 2,620 cases			
UCLA dynamic texture database	160 × 110	50 classes, 75 frames per class		Camera panning	
Dynamic texture (DynTex)	220 × 320	656 sequences, each has 150 frames	Color	Inhomogeneous	Different orientations and speeds
DynTex++		36 classes, total 345 sequences	Video	Varied	
MIT Szummer	170 × 115	7 classes, 120 frames per class		No camera motion	Perspective chirping, spiral
UIUC database	640 × 480	25 classes, 40 images per class		View-point change	Scale difference
Texture library	Varied but high-resolution	17 classes, total 928 images	Color	No	No
CMU Near-Regular Texture (NRT) Database	Image and videos	89 classes, total 5775 images			
Textures under varying illumination, pose and scale (KTH-TIPS) database	1280 × 960 or, 200 × 200	10 classes, 108 Images per class	Color and gray-level	9 different scales	3 in-plane orientations
KTH-TIPS2 material database	1280 × 960	44 classes, total 4608 images; also have another set of 11 classes	Gray-level; have color image of 200 × 200 pixel patches	Variability	Varied pose
Amsterdam Library of Textures (ALOT) database		250 classes, 100 images per class; Also, 12 classes (27500 + images)		3 orientations	4 view-points
UMD Texture database	1280 × 900	25 classes, 40 image per class		No	No
Kylberg texture	576 × 576	28 non-rotated classes, 4 images per class; 28 classes with 12 rotations, 1920 images per class		Have some rotated images	No rotation; 12 rotations

Table 2
Database and respective websites or comments.

Database	Website	Contact group/person	Comments
Columbia-Utrecht Reflectance and Texture (CUReT)	http://www.cs.columbia.edu/CAVE/software/curet/html/about.php	Columbia University and Utrecht University	3 databases: (i) BRDF (bi-directional reflectance distribution function) database; (ii) BRDF parameter database; and (iii) BTF (bi-directional texture function) database
VisTex	http://vismod.media.mit.edu/vismod/imagery/VisionTexture/	MIT Media Lab	Images are grouped according to their contents; Have traditional and non-traditional textures
MeasTex	http://www.texturesynthesis.com/meastex/meastex.html		
PhoTex		Heriot-Watt University at Edinburgh	
OUTex	http://www.outex.oulu.fi/index.php?page=outex_home	University of Oulu, Finland	
Digital Database for Screening Mammography (DDSM)	http://marathon.csee.usf.edu/Mammography/Database.html	UCF	Possibly the best dataset on textures in medical texture analysis
DynTex	http://projects.cwi.nl/dyntex/database.html	European FP6 Network of Excellence MUSCLE	Dynamic texture
PerTex	http://www.macs.hw.ac.uk/texturelab/resources/databases/	Fraser Halley	334 photometric height maps with perceptual similarity matrix

Table 3
Comparison among some photometric texture databases.

Database	Image rotation	3D surface rotation	Illumination	Photometric stereo
Brodatz	Yes	No	Varied	Unregistered
CUReT	Yes	Yes	Controlled	Unregistered
OUTex	Yes	Yes	Controlled	Unregistered
PhoTex	Yes	No	Controlled	Registered
PMTex	Yes	Yes	Controlled	Registered
VisTex	Yes	No	Controlled	Unregistered
MeasTex	Yes	No	Uncontrolled	Unregistered

database in order to provide a richer benchmark for future dynamic texture analysis. The original database is already publicly available; however, only the raw AVI videos are provided. These sequences are filtered, pre-processed, and labeled. While DynTex contains a total of 656 video sequences, DynTex++ uses only 345 of them. It has 36 classes. It means that some sequences are eliminated that contained more than one dynamic texture, contained dynamic background, included panning/zooming, or did not depict much motion. They were not uniformly distributed among the classes. Ref. Ghanem and Ahuja (2010a) obtained an average recognition result of 63.7%. It is a challenging database.

5.6. Temporal Texture Data/MIT Szummer dataset

Temporal Texture Data/MIT Szummer dataset (Otsuka et al., 1998; Peh and Cheong, 2002; Szummer, 1995; Peteri and Chetverikov, 2005; Szummer and Picard, 1996; Zhao and Pietikainen, 2006) is small and the quality of the data in terms of image resolution, contrast, motion stability is quite poor (Fazekas and Chetverikov, 2005; Chan and Vasconcelos, 2007) compare to Peteri and Huskies (2005). Classification results for the 10 Szummer sequences (Szummer, 1995) are accomplished by Peteri and Chetverikov (2005). Temporal textures are textures with motion. The dataset consists of commonly occurring temporal textures, such as river-near (close-up of water), river-far (wide-angle short of water), steam (steam from manhole), boil-heavy (vigorously boiling water), boil-light (lightly boiling water), plastic (windblown plastic sheet), and toilet (swirling water in toilet) (Szummer and Picard, 1996). The image sequences of temporal textures are recorded using a Hi-8 video camera and a tripod is used to ignore any camera motion. The resolution is about 170×115 and the length is 120 frames. This is tough dataset because fluid surfaces are highly specular, and in some cases, perspective chirping is prevalent. The ‘toilet’ image sequences have spiral motion. Fig. 7(b) shows some sequential form ahead.

6. Discussions

In the previous sections, we categorize various texture datasets and pointed important issues regarding their merits, constraints, few comparative discussions. In this section, we summarize some key properties of important textures databases in Table 1. We can notice that in terms of number of classes and variability, there are diverse databases. A number of databases are not developed in controlled and organized manner. For example, the Brodatz database is not organized and scanned from copyrighted book, even though it is the most widely used texture dataset. We can notice at the same time that some databases are available with different image sizes, as the original images are down-scaled for smaller image size. Regarding color or gray-level issue, most of the databases are available in color image formats. As shown in the Table 1, we notice that cameras or sensors are diverse as well. In some cases, various properties are not available in the original paper or respective websites (e.g., in Table 2) – therefore, it is not possible to put all properties comprehensively.

Table 3 presents some comparative properties for datasets that are Photometric Texture Database. In Table 4, we pointed the illumination conditions and camera or sensor details. This Table demonstrates the variation on lighting conditions and cameras, from which we get the notion that it is not easy at all to compare all datasets in single platform. Considering the above-mentioned databases, the future direction could be in the 4D dataset (Woods et al., 2007). The dynamic databases are also not well-organized and lacking a good number of classes. So far, the recognition approaches covering the dynamic textures are very few. Therefore, a more in-depth analysis in this arena is crucial and challenging. Though there are a few well-known databases related to medical texture analysis, several more datasets are presented in some papers though these are not available and not even well-structured. We recommend that some better datasets on texture in medical image processing are required. In future, we are expecting to have a few more challenging datasets for static and dynamic texture. But it is an essential part for the researchers to do comparative researches on the existing datasets by employing various related methods. Note that this task is not trivial and a challenging one

Table 4
Comparisons in terms of illumination and camera/sensors.

Database	Illumination	Camera/sensors
Brodatz	Varied illuminations as photos are taken in different time and places	Scanned images from a book
CUReT	Controlled but 7 illumination directions	Fixed camera with tripod
VisTex	Mixed (daylight, artificial-florescent, artificial-incandescent, & some are imprecise)	Camera (having frontal-plain and oblique settings)
MeasTex	Varied	35 mm camera film, then scanned
PhoTex	40 different illumination directions	Vosskuhler CCD 1300LN digital camera
OUTex	3 illuminations	Sony DXC-755P three chip CCD camera attached to a GMFanuc S-10, a 6-axis industrial robot
MRI Brain	Constant	1.5-T Siemens scanner
DDSM	Constant	Mammograms
MIT Szummer	Varied	Hi-8 video camera
Texture library	Varied	Digital camera
KTH-TIPS	4 illuminations	Olympus C-3030ZOOM digital camera
KTH-TIPS2	3 illuminations	Olympus C-3030ZOOM digital camera
A LOT	8 different illuminations	Sigma SD10, SD9 (c3) Foveon X3 3CMOS camera

due to the fact that these datasets are varied in terms of varieties in classes, per class instances, image resolutions, lighting conditions and angles. Therefore, all datasets may not be covered to compare. The ranges of applications for most of the datasets are understandable from their names, and added discussions provide these issues as well. We feel that the above-mentioned criterions and nomenclature are helpful for further analysis and evaluations.

Another query may appear on what kind of texture datasets seem more important for future research. According to our analysis, it is case-specific and application-dependent. For medical image analysis, the perspectives and necessity are different and crucial respectively. For various materials analysis, it is necessary to under textures for applications in industry, automations and robotics. Understanding an image surface or a material is one of the primitive stages to evaluate a scene for a robot or intelligent system for applications on material evaluation, human action understating, object identification and recognition, etc.

7. Conclusions

This paper is about texture databases. We convincingly categorize texture databases, based on many references. In this survey, we put a nomenclature to split these texture datasets into few basic groups and later put related datasets. We discuss and analyze these in-depth and point some comparative issues. We feel that this paper is a good contribution for the vision community. In future, experimental analysis can be done based on various categories of datasets by employing several algorithms – so that one can analyze them experimentally and understand on what algorithms are more suitable for what kind of textures. We also need to develop few more large datasets, especially in the field of medical image analysis.

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