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| Chapter Proposal for **Digital Image Processing on Gama-Ray and X- Ray Images for Biomedical Applications** |

**Proposed title:**  **Digital Image Processing on Gama-Ray and X- Ray Images for Biomedical Applications**

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# Abstract (142 words)

The purpose of this research book chapter is to investigate the sensitivity of contrast-based textural measurements and morphological characteristics that derive from high-resolution satellite imagery (three-band SPOT-5) when diverse image enhancements techniques are piloted. The general framework of the bio medical application is the built-up/non built-up detection. In the existence of a low-resolution reference layer, we apply supervised learning that indirectly reduces the uncertainty and improves the quality of the reference layer. Based on the new class label assignments, the image histogram is adjusted suitably for the computation of contrast-based textural/morphological features. A case study is presented where we test a mixture of image enhancement operations like linear and de correlation stretching and assess the performance through ROC analysis against available building footprints. Experimental results demonstrate that spectral band combination is the key factor that conditions the contrast of grayscale images. Contrast adjustment (before or after the band combination and merging) supports considerably the extraction of informative features from a low-contrast image; in case of a well-contrasted image,the improvement is marginal.

# Keywords:

Image Enhancement, Bio Medical, Nuclear Medicine, Image Pixel

# Introduction

In the context of contrast-based feature extraction from high-resolution satellite imagery, image enhancement techniques are utilized to modify the band intensities and decrease the noise that covers significant information. Typical image enhancement techniques are as follows: linear contrast adjustment, de correlation stretching, histogram equalization, and adaptive filtering classified as pixel/spatial-based approaches. Fourier decomposition, wavelet transform, and discrete cosine transform are alternative approaches that belong to the frequency-domain techniques. The majority of the aforementioned techniques aim at improving the visual

Inspection of the image and usually involves manual parameter tuning. The requirements of our application, as delineated further down, impose a fully automated approach combined with a low-complexity algorithm for massive image processing. The framework of the specific application is defined by the following considerations and assumptions.

# Background

We will explore the ground for this study shaped from the need of finding a consistent and automatic way for the standardization of the uncelebrated images. Our main goal was to test the sensitivity of contrast-based textural measurements and morphological characteristics when computed over different gray representations. Thereafter, a second objective was the investigation of alternative ways, statistical in their nature, which might provide a suitable means for conducting standardized feature extraction. Accordingly, we present herein some experimental results and we put forward a statistical learning approach for the stabilization of the image contrast sensitivity to different preprocessing conditions

In particular, a simple algorithmic schema is proposed as described briefly below.

1) A binary classifier [support vector machine (SVM)] is trained in the light of a low-resolution reference layer.

2) The optimal hyper plane that separates the two classes:

1) Built-up (BU);

2) Non built-up (NBU) is estimated through a nonlinear mapping.

3) The class labels of the reference layer are modified via *ad hoc* treatment of the respective training samples that delimit the hyper plane into a high-dimensional feature space.

4) A histogram adjustment driven by the reference layer is applied per class. In practice, this turns out to instruct and facilitate mostly the extraction of the textural measurements.

For the needs of supervised learning, we exploited the existence of the soil sealing layer (SSL). This is a raster dataset of European areas providing information of the degree of soil sealing in aggregated spatial resolution of 100 m *×* 100 m [11]. Main traits of the specific product are its completeness and its relatively high overall accuracy, observed largely in dense BU areas [12]. The proposed approach constitutes a data preparation phase just before the feature extraction. It attempts to improve the quality of the textural/morphological characteristics while retaining the computational burden in low levels. Generally speaking, it moves inside the concept of synergy between machine learning and image processing; one contiguous application has been presented recently in [13]. This paper is organized as follows. Section II describes the algorithmic schema, the assumptions, and the parameterization. Section III explains the experimental setup; results are demonstrated for the city of Torino, Italy, while the performance is assessed through *ROC* analysis with the aid of a footprint layer at 2.5-m spatial resolution. Section IV discusses the findings of the experimental study and Section V summarizes and provides suggestions for future work.

**Biomedical Image Features:**

The textural measurements we are interested in are estimated through the Hurlock’s measure for the intensity contrast between a pixel and its neighbors [9]. The factors (quantization, length, and orientation) and the operators like fuzzy composition are defined in [8]; the produced textural layer is known as PANTEX.

Regarding the morphological features, we included in our tests a recently introduced index named *morphological building index* (MBI) [5], [7]. It is a quite accurate indicator that considers the characteristics of buildings (brightness, size, contrast, directionality, and shape) by integrating multi scale and multidirectional morphological operators. Note that both PANTEX and MBI are automatic indices and their operation is not based on statistical learning and training samples.

Trying to reduce the high dimensionality of the co occurrence matrix over which the textural measurements are computed, we convert the multiband images to 8-bit grayscale. Besides, the gray level images are suitable to work with morphological operators. The challenge now is to adjust selectively the image intensities, so that the difference between the pixel values that refer to BU and NBU to be as high as possible; in this manner, the BU representation becomes distinguishable. The contrast adjustment can be done either during the image conversion to grayscale by means of a suitable spectral band combination or by modifying the histogram of the image intensities.

# Image Analysis

Image analysis accepts a digital image as input and produces data or a report of some type. The produced data may be the features that represent the object or objects in the input image. To produce such features, different processes must be performed that include segmentation, boundary extraction, silhouette extraction, and feature extraction. The produced features may be quantitative measures, such as moment invariants, and Fourier descriptors, or even symbols, such as regular geometrical primitives.

**Gamma-Ray Imaging**

Major uses of imaging based on gamma rays include nuclear medicine and astronomical observations. In nuclear medicine, the approach is to inject a patient with a radioactive isotope that emits gamma rays as it decays. Images are produced from the emissions collected by gamma ray detectors. Figure 1.6(a) shows an image of a complete bone scan obtained by using gamma-ray imaging. Images of this sort are used to locate sites of bone pathology, such as infections





**FIGURE 1.6** Examples ofgamma-rayimaging. (a) Bonescan. (b) PETimage. (c) CygnusLoop. (d) Gammaradiation (brightspot) from areactor valve.(Images courtesyof (a) G.E.Medical Systems,(b) Dr. MichaelE. Casey, CTIPET Systems,(c) NASA,(d) ProfessorsZhong He andDavid K.Wehe,University ofMichigan.)

or tumors. Figure 1.6(b) shows another major modality of nuclear imaging called positron emission tomography (PET).The principle is the same as with X-ray tomography, mentioned briefly in Section 1.2. However, instead of using an external source of X-ray energy, the patient is given a radioactive isotope that emits positrons as it decays.When a positron meets an electron, both are annihilated and two gamma rays are given off.These are detected and a tomographic image is created using the basic principles of tomography. The image shown in Fig. 1.6(b) is one sample of a sequence that constitutes a 3-D rendition of the patient.This image shows a tumor in the brain and one in the lung, easily visible as small white masses.

A star in the constellation of Cygnus exploded about 15,000 years ago, generating a superheated stationary gas cloud (known as the Cygnus Loop) that glows in a spectacular array of colors. Figure 1.6(c) shows an image of the Cygnus Loop in the gamma-ray band. Unlike the two examples in Figs. 1.6(a) and (b), this image was obtained using the natural radiation of the object being imaged. Finally, Fig. 1.6(d) shows an image of gamma radiation from a valve in a nuclear reactor. An area of strong radiation is seen in the lower left side of the image.

**X-Ray Imaging**

X-rays are among the oldest sources of EM radiation used for imaging. The best known use of X-rays is medical diagnostics, but they also are used extensively in industry and other areas, like astronomy. X-rays for medical and industrial imaging are generated using an X-ray tube, which is a vacuum tube with a cathode and anode. The cathode is heated, causing free electrons to be released. These electrons flow at high speed to the positively charged anode.

When the electrons strike a nucleus, energy is released in the form of X-ray radiation. The energy (penetrating power) of X-rays is controlled by a voltage applied across the anode, and by a current applied to the filament in the

cathode. Figure 1.7(a) shows a familiar chest X-ray generated simply by placing the patient between an X-ray source and a film sensitive to X-ray energy.

The intensity of the X-rays is modified by absorption as they pass through the patient, and the resulting energy falling on the film develops it, much in the same way that light develops photographic film. In digital radiography, digital images are obtained by one of two methods: (1) by digitizing X-ray films; or (2) by having the X-rays that pass through the patient fall directly onto devices (such as a phosphor screen) that convert X-rays to light. The light signal in turn is captured by a light-sensitive digitizing system. We discuss digitization in more detail in Chapters 2 and 4.

Angiography is another major application in an area called contrast enhancement radiography. This procedure is used to obtain images (called *angiograms*) of blood vessels. A catheter (a small, flexible, hollow tube) is inserted, for example, into an artery or vein in the groin. The catheter is threaded into the blood vessel and guided to the area to be studied. When the catheter reaches the site under investigation, an X-ray contrast medium is injected through the tube. This enhances contrast of the blood vessels and enables the radiologist to see any irregularities or blockages. Figure 1.7(b) shows an example of an aortic angiogram. The catheter can be seen being inserted into the



**FIGURE 1.7** Examples of X-ray imaging. (a) Chest X-ray. (b) Aortic angiogram. (c) Head CT. (d) Circuit boards. (e) Cygnus Loop. (Images courtesy of (a) and (c) Dr. David R. Pickens, Dept. of Radiology & Radiological Sciences, Vanderbilt University Medical Center; (b) Dr.Thomas R. Gest, Division of Anatomical Sciences, and University of Michigan Medical School; (d) Mr. Joseph E. Pascente, Lixi, Inc.; and (e) NASA.)

Large blood vessel on the lower left of the picture. Note the high contrast of the large vessel as the contrast medium flows up in the direction of the kidneys, which are also visible in the image. As discussed in Chapter 2, angiography is a major area of digital image processing, where image subtraction is used to enhance further the blood vessels being studied. Another important use of X-rays in medical imaging is computerized axial tomography (CAT). Due to their resolution and 3-D capabilities, CAT scans revolutionized medicine from the moment they first became available in the early 1970s. As noted in Section 1.2, each CAT image is a “slice” taken perpendicularly through the patient. Numerous slices are generated as the patient is moved in a longitudinal direction.The ensemble of such images constitutes a 3-D rendition of the inside of the body, with the longitudinal resolution being proportional to the number of slice images taken. Figure 1.7(c) shows a typical head CAT slice image.

Techniques similar to the ones just discussed, but generally involving higherenergy X-rays, are applicable in industrial processes. Figure 1.7(d) shows an X-ray image of an electronic circuit board. Such images, representative of literally hundreds of industrial applications of X-rays, are used to examine circuit boards for flaws in manufacturing, such as missing components or broken traces. Industrial CAT scans are useful when the parts can be penetrated by X-rays, such as in plastic assemblies, and even large bodies, like solid-propellant rocket motors. Figure 1.7(e) shows an example of X-ray imaging in astronomy.This image is the Cygnus Loop of Fig. 1.6(c), but imaged this time in the X-ray band.

# Future Trends and Conclusion

We are identifying the non ridged ice floe in the marginal ice zone, and the managed ice resulting from offshore operations in sea ice, we proposed an application to identify the individual ice floes in a sea-ice image using the GVF snake algorithm. To evolve the GVF snake automatically, “light ice” and “dark ice” were first obtained using the thresholding and *k*-means algorithms. The initial contours of both “light ice” and “dark ice” with proper locations and radii were then derived based on the local maxima from the distance transform. After ice edge detection, morphological cleaning was used to enhance floe shapes. The implementation on the sea-ice images, which contained multiple ice floes crowded together, is shown to give acceptable segmentation results.

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