Fusion of real and synthetic images for remote sensing scene understanding

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The high complexity of remotely sensed images and measurements, provided by the last generation of sensors, demands new techniques for scene understanding and analysis. The paper introduces topics in multisensor and synthetic images fusion. The fractal geometry is applied for unknown information modelling. Integrated techniques in computer graphics and computer vision are used. A new method is introduced for more accurate representation and visualisation of the fractal surfaces. A multiresolution approach is considered for the accurate description of surface radiometry and geometry. The image synthesis is based on the knowledge of surface geometry, on radiation source, and sensor characteristics, and on the radiation scattering process for different cover types. In the final part, results of the developed techniques are applied in satellite imagery understanding.

Keyword Codes: I.2.10; I.3.3; G.m
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1. INTRODUCTION

The last generation of Earth Observation Satellites is characterised by a multitude of sensor types covering a large domain of spectral sensitivity and spatial resolution. The usual sensors range from visible, infrared to microwave spectrum, covering coherent or non-coherent radiation, with spatial resolution from meters to kilometres. In the mean time, the huge complexity of land-forms and land-cover types is reflected in the complexity of the recorded images. As consequence the interpretation of remotely sensed data faces with difficulties concerning scene understanding. Attractive solutions are model based inferences, and multisensor data fusion.

As an illustrative example, the merging of two images from two different sensors, is given in figure 1. The image acquired by an optical sensor system showing an area heavily obscured by clouds is partially substituted by radar data acquired at the same period of time.

The process of image understanding always asks interpretation using some prior knowledge about the scene and the imaging process. The prior knowledge can be expressed in terms of models. In each case the model may be used to interpret the original image.
The similarity of fractal and real world objects was observed and intensively studied from the very beginning. The fractal geometry became a tool for computer graphics and data visualisation in the simulation of the real world. In order to perform visual analysis and comparisons between natural and synthetic scenes, several techniques have been developed. After a period of qualitative experiments fractal geometry began to be used for objective and accurate purposes: modelling the image formation process, generation of geometrically and radiometrically accurate synthetic scenes and images, evaluation of the characteristics of the relief,
determination of the surface roughness, analysis of textures. The techniques based on fractals show promising results in the fields of image understanding and visualisation of high complexity data.

2. FUSION OF REAL AND SYNTHETIC IMAGES

The fusion of information from multiple sources is an increasingly important area of research and application. The information to be fused originates from sources of different types and is expected to give complementary description of the envisaged process. The objective of data fusion is to determine an estimate of scene structure identity. A direct paradigm for performing identity declarations is the use of physical models. The model aims to predict the scene identity is based on the knowledge of the physics of the candidate scene. The physical identity declaration process compares, in terms of correlation for example, the observed data against a simulated signature [1,2]. The concept is illustrated in figure 2. For the understanding of remotely sensed scenes the data to be fused are real images and non-image data. The image data are usually required in complementary spectral bands. The non-image data, as the Digital Elevation Model of the imaged area, and the knowledge of the image formation process are the base for model generation. Due to the imaging geometry and the sensor characteristics, a first fusion level is reached for the geometric corrections. A second level of data fusion cumulates the information available concerning the description of the physics of the image formation, and represents these data in synthetically generated images. Further, in a third fusion level, the synthetically generated images, in a model based inference, are used for scene identification.

Figure 2. Multisensor and synthetic image fusion

Unfortunately, for high complexity scenes, even multisensor data can be incomplete. To deal with incomplete data, in the image formation process, fractal geometry can be used when models are unknown. The proved self-similarity or self-affinity of the land-forms and land cover structures are used. In figure 3 the synthesis technique is shown.
The lack of geometric data encoded in Digital Elevation Models (DEM) and radiometric information is supplemented using fractal objects. The data fusion from real satellite images with synthetic images creates a new approach in model based image understanding. The model is expressed in terms of the geometry and radiometry of the synthetic images. The concept of identity declaration by physical modelling is considered.

3. SYNTHETIC IMAGES: APPLICATIONS OF FRACTAL GEOMETRY

Many of the early applications of fractal geometry were involved in finding methods for the generation of pleasant visual aspect images for computer graphic representations. More recently realistic looking landscapes have been synthesised for flight simulators or relief visualisation of other planets [3], and more precise simulations of the landforms are derived in the aim to build models to be used in feature evaluation for further correlation with characteristics of the natural relief [4]. Geomorphology and soil science ask for terrain models with peculiar characteristics for other simulations: water erosion process, drainage basins topology, surface water flow, river’s course erosion, wind mass transport effects, deforestations, volcanic lava flow [5, 6]. One of the benefits in cartography from fractal simulation is the possibility to generate synthetic digital elevation models at a variety of scales and terrain roughnesses which can be used as test areas for the performance of the algorithms for digitizing simulated cartographic maps [7]. The techniques frequently used for the generation of synthetic DEMs are the midpoint displacement, and the simulation of the $1/f$ noise. A Gaussian white noise is filtered using a $1/f^\beta$ shaped transfer function. The output signal is a self-affine fractal having the fractal dimension $D = T + (3 - \beta)/2$. $T$ is the topologic dimension of the space [8]. Figure 4 shows two synthetic DEMs having different fractal dimension. The surfaces are presented as Lambertian surfaces illuminated from the S-E direction. The left side image, 4a, due to the fractal behaviour, can be considered as any rescaled subwindow from the right side image, 4b. The surface is self-affine, in statistical sense. The lakes in the right side image are obtained as the intersection of a plane with the surface. The contours of the lakes are fractal lines having the fractal dimension $D - 1$ [9].
Available DEMs are generally limited in resolution. The resolution is given by the constant of the support grid for the height data. Applications as: relief visualisation, image formation modelling for remote sensors, high resolution contour mapping, ask accurate DEMs. A higher resolution can be obtained by a resampling process: to add new samples in a higher resolution grid. If functional resampling is used the resulting DEM has an unrealistic smooth aspect. It was experimentally proved that the natural relief has fractal behaviour for a certain range of scales [10, 11]. The fractal resampling process uses this prior information: the similarity of landforms for several spatial scales. The fractal resampling is accomplished in two steps: the analysis of the real DEM for evaluation of the fractal dimension and local variance of the height field, and the fractal interpolation [12]. The fractal interpolation increases the resolution of the DEM in steps of 2. The statistical resemblance of the synthesised samples is obtained using the random addition method of Voss [13]. An example is presented in figure 5: an 100 m resolution DEM resampled to 50 m. The surface is presented as a Lambertian one, lighted from S-E. The visual appearance is more realistic but not only, other applications where the exactitude of the DEM is required in stochastic sense are of practical importance. The generation of synthetical images in the aim to enhance the performance of classification for remotely sensed images is one of the topics of interest [14]. The fractal resampling can not be applied down a given scale. Gravity and diffusion process or, vegetation cover broke the continuity in similarity, and other models must be applied [15].

4. MULTRESOLUTION APPROACH IN IMAGE SYNTHESIS

Surface visualisation is limited in accuracy for at least two reasons: the limited resolution of the geometrical description, and incomplete knowledge and imperfect simulation of the light scattering process. For surfaces having fractal behaviours any i facet or interpolated representation means a cut in the similarity. A multiresolution approach is used to derive an accurate model [16]:

Figure 4. Synthetic fractal DEMs presented as Lambertian surface illuminated from S-E.
1. At macro-scale the scene is described by the knowledge of the surface geometry.
2. A meso-scale is introduced relative to the spatial resolution of the sensor. The pixel intensity is dependent on the local geometry, on the local roughness of surface at a resolution higher than the sensor’s geometrical resolution, and on the reflectance behaviours of the surface at next finer scale. Thus the sensed intensity is the result of a nonlinear spatial operator. This spatial operator models the image formation process of the specific sensor.
3. At micro-scale the facets of the surface are characterized by reflectance functions. They are generally obtained by statistical, experimental or on heuristic basis.

The realism and accuracy of the synthetic images is determined by the model of local light scattering. A general scattering function for unpolarized light (figure 6) is a function of the four variables, the Bidirectional Reflectance Function, BRF [17].

\[
\rho_{bd}(\theta_i, \Phi_i, \theta_r, \Phi_r) : B \rightarrow B
\]

Where B is the unit ball, \( \theta_i \) and \( \Phi_i \) are the elevation and azimuth incidence angles, and \( \theta_r \) and \( \Phi_r \) are the elevation and azimuth reflectance angles.

At micro-scale the BRF can be approximated from simple models of light scattering. The model is dependent on three physical parameters describing the surface appearance: diffuseness, specularity and interreflection characteristics.
The perfect diffuse reflection, the Lambertian assumption, supposes that light is uniformly scattered. This is the first component of the developed model. The reflected light intensity is proportional to the cosine of the incidence angle. For a planar surface illuminated by N distinct sources the sensed intensity, \( I_{\text{diffuse}} \) is independent from the viewing direction (figure 7).

\[
I_{\text{diffuse}} = k_d C_s \sum_{j=1}^{N} I_j \cos(\hat{n}, \hat{l}_j)
\]

Figure 7. Diffuse reflection.

Where \( k_d \) is the diffuse reflection coefficient, \( C_s \) is a coefficient related to the surface spectral characteristics, \( \hat{n} \) is the local surface normal, \( I_j \) is the intensity of the j source, and \( \hat{l}_j \) are the incidence vectors.

The second component of the model is the specular reflection process (figure 8).

\[
I_{\text{specular}} = k_s C_s \sum_{i=1}^{N} p_i I_j \cos(\hat{n}, \hat{h}_j)
\]

Figure 8. Specular reflection.

Where \( p \) depends on the surface glossyness, \( k_s \) is the specular reflection coefficient, and \( \hat{h}_j \) is the vector in the direction of the bisector line between the observer and the j\(^{th}\) light source.

The third component of the model is the interreflection process (figure 9). One consider all the possible specular reflections between the facets of the surface. The resulting amount of interreflections depends on the geometry of the surface at macro-scale, on the position of the light source, and on the ray extinction at each reflection. The model assumes only one level of interreflections.

Figure 9. Interreflection process

At meso-scale the previously presented models and the sensor description are considered. The image formation process is simulated. The sensor is represented by a non-linear spatial operator. In the usual case the operator is a spatial convolution of the surface reflectance with the point spread function of the sensor followed by a non-linear transform.

If the sensor resolution is lower than the resolution of the surface, the intensity of one pixel is modelled by the integral of all scattered intensities of the microfacets weighted by the sensor’s spread point function. A virtual radiometric experiment can be carried out for a given
sensor and micro-geometry of the surface. In figure 10a the imaging geometry for a rough surface is presented. Each microfacet is characterised by the surface optical attributes and its geometry, the local normal vector \( \vec{n} \). The sensor and source of light positions are specified respectively by the vectors \( \vec{v} \) and \( \vec{l} \). An area of 32 x 32 microfacets was imaged from a nadir placed sensor with variable incident illumination. The resulting images are displayed in figure 10b. The last scene is a perspective view of the imaged surface (3D). Using the information from these images the albedo and BRF have been computed, and with prior knowledge of the sensor characteristics the accurate pixels intensities have been modelled.

The experiment explains the difference in radiometry of the images in figure 5. After a fractal resampling the local roughness increases and the BRF is modified. The experiment was applied for vegetation cover radiometric evaluation. A three dimensional plant model was developed using generalised L-systems [18].

To take into account the exact surface roughness and to calculate the actual scattering crosssection the Kirchoff solution must be found. The validity of Kirchoff solution was intensively studied [19]. In the solution of scattering from fractal surfaces, the wavelength is considered as yardstick. The solution is derived for relative space-scale to wavelength ratios [20]. The results find applicability to synthetic aperture radar (SAR) imagery of sea surface or rough terrain.

![Figure 10. Imaging geometry, rough surface imaged for different incident light position; 0, 15, 30, 45, 60, 75, 90 degr., and 3D view.](image)

5. FRACTAL SURFACES VISUALISATION

The intrinsic similarity of the fractal surfaces for an infinite range of scales makes an accurate visualisation impossible. Applying the simple models presented in chapter 4, and using the knowledge of the surface geometry at meso-scale and the sensor model, complex and more accurate reflectance functions have been obtained. The virtual radiometric experiment was applied for fractal surfaces.

Figures 11 a, b, and c show the dependence of the sensed intensity on the roughness, \( \gamma \), and
on the incidence light angle, $\alpha$, for three different assumptions of the micro-scale facets appearance: diffuse (a), diffuse and specular (b), and diffuse, specular, and interreflections (c). Note that the highest roughness is for low values of $\gamma$ (highest fractal dimension).

![Figure 11. Reflectance functions](image1)

In figure 12 fractal surfaces are shown in macro-scale representation with diffuse and specular appearance. Figure 12a is generated with the appearance of the microfacets described by the diagram in figure 11a, and image 12b with the reflectance function as shown in figure 11b.

![Figure 12. Fractal surface visualisation](image2)

*Figure 12. Fractal surface visualisation*

a - Lambertian BRF  
b - BRF embedding multiscale information
6. APPLICATIONS IN UNDERSTANDING OF REMOTELY SENSED IMAGES

The data fused in synthetic images, and the modelling of incomplete knowledge using fractal objects, is further demonstrated in a remote sensing application. The aim is to segment the snow covered areas in rough mountainous regions. This results in a new method for the rejection of topographic influences in the radiometry.

The importance of topographic effects on the radiometric behavior of the remotely sensed imagery increases for at least two reasons: the higher spatial resolution in the latest generation of satellite sensors, and the extension on remote sensing applications to rough mountainous areas. The higher spatial resolution of aerial imagery makes the analysis more sensitive to local terrain roughness. Interpretation of mountainous regions faces one with difficulties during classification due to shadow areas and diffuse and indirect secondary lighting. The existing methods for the alleviation of topographical effects are based on models for light scattering that are local, implying that the model does not take into account the spatial resolution of the sensor, and the DEM resolution.

![Figure 13. a - DEM, perspective view, b - synthetic image, c - Landsat TM image, d - radiometric correction of topography influences.](image)
The previously deduced results in the virtual radiometric experiments have been used as base for a physical model multisensor image and data fusion inference. Digital Elevation Models (DEM) of adequate resolution are available. This makes attractive the idea of geometrical modelling of the satellite images. Model refers to the geometry, to the radiometry of the imaged scene, and the simulation of the image formation process, the sensor and illumination models [21].

To alleviate the influences of the topography in a satellite image of a rough mountain area, synthetic images have been generated. For this experiment a Landsat TM scene, band 4 (figure 13), was used. The spatial resolution of the sensor is approximately 30 meter. The data and knowledge fused in the synthetic image are: the geometry of the terrain, the sensor model, the sun position and an illumination model, the multiresolution assumption in image formation. The geometry is described by a Digital Elevation Model known in a 10 meter rectangular grid. The sensor was modelled by a convolution operator. The sun elevation and azimuth at the date and time of image acquisition are used. The illumination model is defined for direct lighted and shaded areas. Parallel illumination, illumination by interreflections, and diffuse light are considered. At micro-scale, 10 meters resolution, the surface is assumed to be described by diffuse, specular reflections and interreflections. At meso-scale, 30 meters resolution, the sensor model was used to deduce the pixel intensity.

In figure 13 are presented: a) the perspective view of the DEM, b) the synthetic image modelling the snow cover, this image can be interpreted as a visualisation of the fused data, c) the Landsat TM band 4 scene, and d) the segmentation of the snow cover in the previous image. The radiometry of the synthetic image models rough surfaces covered by snow. Due to the more complete model specification, the accuracy obtained in snow cover segmentation is superior to other methods [22]. The presented algorithm describes the image formation process for direct lighted, and shadow areas, using the multiresolution approach.

7. CONCLUSIONS

The paper presents two topics in data fusion, the utilisation of fractal geometry for the simulation of incomplete data, and the data and knowledge fusion in synthetic images. The introduced method is an extension of the physical model inference in data fusion. The scene identification is accomplished by a second level of fusion of the real and synthetic images. The multiresolution approach in image synthesis is used to accurately represent and visualise surfaces with fractal nature. The similarity of fractal and real world is used as base for incomplete knowledge modelling, and the results are applied for remotely sensed image processing. Better results have been obtained in the alleviation of the radiometric effects induced by the topography in the imagery of rough terrain regions.

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