A novel extension of the anisotropic rotation-invariant built-up presence index to SAR data

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Abstract
Although the mechanisms underlying remote sensing images by optical and SAR sensors are very different, specific environments are represented on both types of imagery as largely similar spatial patterns. The anisotropic rotation-invariant built-up presence index makes use of these patterns on optical imagery for delineating and characterizing human settlements. This paper focuses on the necessity of a different definition for this index when it is applied to SAR data. Although the extension from optical to radar data is not straightforward, the formulation proposed in this paper makes it suitable for a good characterization of large urban areas and small informal settlements as well.
After introducing and validating the slant-range version of the anisotropic rotation-invariant built-up presence index, a comparison of its effectiveness with respect to different radar viewing geometries and frequencies on the same test area is carried out, suggesting that the methodology works well in any situation.

Keywords: SAR, built-up area extraction, urban remote sensing.

Introduction
Although spectral characteristics of human settlements vary between and within the built-up area, their spatial patterns are distinctively different from most natural surfaces. This statement is fundamental to many algorithms designed for urban remote sensing analysis. They are usually introduced in the form of indexes, for instance to detect the presence of built-up areas or to analyze their structure or to provide land use/land cover maps. All of these approaches are indeed based on spatial analysis of the data, considering for instance different textural [Haralick et al., 1973; Baraldi and Parmiggiani, 189995; Dell’Acqua and Gamba, 2003; ] or statistical [Gouinaud and Tupin; 1996, He et al., 2006] measures. Alternatively, multi-temporal information may be exploited, such as coherence and amplitude in SAR imagery [Liao et al., 2008]. However, many of the approaches introduced have been applied and discussed on a single data set, i.e. on one individual urban area using a single sensor [Henderson, 1975; Henderson, 1979] under specific viewing and illumination conditions. This effect is quite critical for SAR data and known since long time [Bryan, 1979; Hardaway et al., 1982], but never fully analyzed with respect to classification accuracy. Moreover, in many cases extensive cross-validation with other approaches is missing. Other methodologies, which have been proposed for built-up area extraction, use more complex schemes [Soergel et al., 2004, Huang et al., 2007; Unsalan, 2007].
Even though they are valuable, they tend to be less robust for use with different data sets or very complex to be implemented and/or trained.

In Pesaresi et al. [2007] a very simple, yet robust algorithm for built-up area detection was proposed, the anisotropic rotation-invariant built-up presence index. This index has originally been designed for use with optical images, with the specific goal to be robust to noise, data compression problems, and errors in data calibration. The main difference of this approach with respect to those mentioned above is the choice of the textural measures and the way more textures are combined to discard false positives, as well as the simplicity and straightforward implementation of the algorithm.

The work shown in this paper is aimed at proving that this index can also be applied, although not in a straightforward manner, for the analysis of SAR intensity data with suitably fine spatial resolution. To this end, a definition of the index in the original slant-range geometry of SAR data is required to achieve results comparable with those with the original formulation and optical data.

A new formulation for the anisotropic rotation invariant built-up presence index

The original formulation of the anisotropic rotation-invariant built-up presence index [named “PanTex” in Pesaresi et al., 2008] is based on the concept that built-up structures are of a certain dimension and can be discriminated from the background by their known spatial relationships. Additionally, the representation of built-up structures in the imagery is, to some extent, anisotropic at the scale of the urban area.

Therefore, as opposed to more traditional approaches, for this index a number of different displacement vectors are evaluated to exploit the anisotropic nature of the urban texture. The set of displacement vectors to be used may be determined based on average building size and the spatial resolution of the remotely sensed data set. For instance, in the case of standard built-up structures having side sizes ranging from 10 to 20 meters and an input image at 5 m spatial resolution, we expect to have good response of the textural measure based on a distance parameter of d=1 and d=2 pixels. This value takes into consideration the requirement of being able to capture the contrast between building roof and background and the building shadow interval. Since the co-occurrence matrix is symmetric, this yields a total of 10 displacement vectors to be used. Some of them are shown in Figure 1 (a).

According to Pesaresi [2000], these displacement vectors are used to compute the GLCM (Gray Level Co-Occurrence Matrix) parameter “contrast” with the following formula:

\[
CON = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i-j)^2 p_{ij} \quad [1]
\]

where \(N_g\) is the number of gray levels present in the image, and \(p_{ij}\) is the (\(i,j\))-th entry of the co-occurrence matrix. Finally, the results for different displacement vectors are combined by means of the min operator (i.e. a logic AND). In fact, it has been demonstrated [Pesaresi, 2000] that deriving the rotation-invariant texture measure by integrating the individual direction parameters based on min and max operators is superior to averaging the individual channels. This formulation may be applied to multi-look georeferenced SAR intensity
images in addition to optical data. While the land use-specific statistics are different, the spatial patterns in urban areas are similar. However, SAR data are acquired in slant-range geometry and are reprojected to ground-range geometry during georeferencing. As a result of the resampling performed during reprojection, the appearance of small targets is altered. Although they may be well visible in the original data, their contrast with respect to the background is usually smaller. Thus, the projection step usually reduces the possibility to detect small settlements and/or man-made structures. It also changes the textural and statistical properties of the data, and it is good practice to perform textural analysis of SAR data in their original slant-range geometry [Oliver and Quegan, 1998].

![Figure 1 - A few examples of displacement vectors in a 5 x 5 pixel square kernel that can be used for the original PanTex formulation for optical imagery (a) and the corresponding 9 x 5 kernel to be applied to the SAR slant-range data (b) with spatial resolution of 4.63 x 5.29 m.](image-url)

Therefore, a modified version of PanTex has been developed. It basically redefines the window dimensions and the evaluated displacement vectors used for contrast computation (see Fig. 1b). This implementation is thus suited to the slant-range pixel size and calculates the index before the ground-range reprojection is performed. In accordance with this new definition, the algorithm follows these processing steps.

- The displacement vector set designed to match a the specific urban target is mapped onto a rectangular kernel, according to the (variable) sampling of the SAR data in azimuth and range.
- The computation of the contrast texture measure for the displacement vector set is then based on the rectangular matrix window. The approach has been implemented as a computationally efficient program which decreases considerably the processing time with respect to the usual window-based approach and computes simultaneously most of the basic computational elements of the textures for different displacement vectors.
- The third step is a scaling and feature integration using the min operator, which is performed similarly to the original PanTex implementation.
- Finally, a slant-to-ground projection is applied to get a ground range version of the index.
In Figure 2 the new approach is illustrated. It has to be noted that the slant-range implementation will result in a different range of index values compared to the index computed directly on the ground-range data set. This is a result of the different representation of similar image textures on single-look data vs. resampled multilook imagery, due to the non-linear nature of the slant- to ground-range transformation. The process involved in transforming a SAR image from slant range to ground range involves a loss of information. This will reflect on a more faithful result in processing directly the original slant range dataset. The proposed approach has been designed for SAR slant range data, so that it can fully exploit its finer spatial resolution. Applying it to multilook data will reduce its effectiveness. Moreover, small targets (e.g. isolated houses) are less visible in multilook images, because of the smoothing effect, thus providing an additional reason for the reduced effectiveness of the approach on those images.

**Figure 2 - A comparative graphic representation of the steps involved in computing the original and “slant-range” PanTex.**

**Experimental results**
The radar satellite data used to evaluate “slant-range” PanTex are summarized in Table 1. They were acquired by RADARSAT-1 (Canada) and by the PALSAR sensor on ALOS (Japan) over the urban area of Nairobi (Kenya). The RADARSAT-1 images were both acquired in Fine Mode and in a descending pass, but using two different beams, i.e. different viewing geometries or incidence angles. The ALOS-PALSAR image was acquired on an ascending pass with a slightly smaller incidence angle. Thus, SAR data of different frequencies (C- and L-band respectively), but of similar ground-range spatial resolutions are considered.

In order to evaluate the impact which the two different implementations have on the detectability of built-up structures, two radiometrically different subsets of the image have been selected for comparison. The first test site is a district in central Nairobi. The area is highly urbanized, and most of the elements in the scenes are roads and buildings, except for a golf course. The second test site is an area located in the outskirts of Nairobi and is characterized by scattered
settlements and isolated buildings. These are represented on the SAR image as individual bright points, clearly outlined and not extending beyond a few pixels. Figure 3 depicts a sample of the first and the second area, as well as the “slant-range” PanTex. It is clear that it detects well each individual building and retains the full spatial accuracy of the original SAR data. Just for comparison in Figure 3 (e) the original PanTex is proposed. The resampling during orthorectification attenuates the building backscattering signatures to an extent where a texture-based index cannot capture them any longer.

Table 1 - SAR data sets about the Nairobi area used in this work.

| Acqu. Date      | RADARSAT-1 F2D | RADARSAT-1 F5D | ALOS      |
|-----------------|----------------|----------------|-----------|
| Acq. Date       | Nov. 09, 2006  | Nov. 16, 2006  | June 22, 2007 |
| Orbit           | Desc.          | Desc.          | Asc.      |
| Look            | Right          | Right          | Right     |
| Incid. Angle    | 40.5°          | 46°            | 34.3°     |
| Polarization    | HH             | HH             | HH        |
| Frequency       | C-band         | C-band         | L-band    |
| Processing      | SLC            | SLC            | FBS       |
| Posting (m)     | 8              | 8              | 6.25      |

Figure 3 - Two samples of the central district (a) and urban fringe (b) areas used to validate the “slant-range” PanTex, depicted in (c) and (d) respectively; (e) original PanTex values computed for (b).
Human settlement detection in the entire scene

Although the richness of the slant-range PanTex is best captured by considering its full range, its most simple and straightforward application is binary human settlement detection and urban extent delineation. This was the original application of the index calculated on multi-temporal panchromatic images, and it can be also useful in SAR data. Radar sensors can obtain data over urban areas in parts of the world where optical images are difficult to acquire. One example is the South of China, where the Chinese National Land Cover Mapping project specifically requested the use of RADARSAT-1 images [Zhang and Zhang, 2007] as opposed to Landsat data which were used for the rest of the country.

It is therefore of importance to start the slant-range PanTex evaluation with a town-scale analysis aimed at the delineation of the urban area of Nairobi as well as nearby settlements. Two problems, however, arise. The first one is algorithmic, and concerns the definition of the appropriate threshold to discriminate between pixels belonging to “built-up” or to “non-built-up” areas. The second problem arises from the need of a validation or at least a cross-reference data set to evaluate and discuss results obtained.

The approach used in this work for finding the appropriate threshold requires the use of some training areas data, belonging to the “Built-Up” (BU) and “Non-Built Up” (NBU) classes. These areas of reference have been selected choosing pure built-up and not-built-up areas present in the study area, in order to minimize the semantic noise. Consequently, only compact high-density built-up areas in the city have been selected as BU reference, and only homogenous natural and agricultural areas with no built-up structures have been selected as NBU reference. Tests made on the robustness of the method, moving the threshold value around the best one show that value around 15% of the best one entail negligible differences on accuracy indexes. Based on the a posteriori class probability density functions (relative frequency histogram) which have been empirically derived using a kernel density estimation, the optimum threshold corresponds to the value of the textural index where we minimize the area of intersection of the two frequency histograms. This point corresponds to the point of intersection of the probability density functions. To minimize sensitivity to the sample size, alternatively, the maximum difference of the associated cumulative probability density functions can be used for deriving the threshold as well.

Qualitative analysis

Global human settlement or land cover projects, as well as regional data sets can be used as reference data for a first, qualitative validation of the results. In this work this goal is achieved by comparison with the maps published by the GlobCover project. GlobCover maps are obtained by classifying optical data from the MERIS sensor and are far more detailed than what is needed here. Only human settlement information is retained. The settlement extent masks obtained from the full RADARSAT F2d and F5d scenes, as well as for the PALSAR scene, are shown in Figure 4. The GlobCover extents for the same area are also shown in the figure.

The reference data set delineate contiguous urbanized regions, while the index proposed in this work detects specifically built-up areas. In doing so, it omits larger non-built-up areas within, such as bare ground or green spaces. Figure 4 shows that PanTex derived human settlement maps exhibit a degree of “porousness” which corresponds to the true land cover but is not classified separately in the reference maps. What we want to stress here is instead that the slant-range PanTex is subject to errors where rock or vegetation formations give rise
to backscattering patterns similar to human settlements. This is visible, for instance, in Figure 4 (a)-(c) for the Northern area of Nairobi, characterized by sparse buildings.

Because of the above mentioned difference between slant range PanTex extents and reference data, the only meaningful comparison between GlobCover and PanTex urban extents is a qualitative, more than a strictly quantitative one. Overall accuracy values are shown in Table...
and were computed considering different window sizes for GLCM computation, i.e. areas of 11 x 10, 21 x 19, and 42 x 40 pixels, corresponding to nearly 50 x 50, 100 x 100, and 200 x 200 square meters. They show a general trend towards increasing accuracy with larger windows, which is consistent with the small scale of the GlobCover reference maps.

Table 2 - Slant range PanTex urban extent evaluation.

| Data set | w= 50 m | w = 100 m | w = 200 m |
|----------|---------|-----------|-----------|
| F2D      | 58.90 % | 59.90 %   | 62.80 %   |
| F5D      | 54.90 % | 54.98 %   | 60.22 %   |
| ALOS     | 65.41 % | 66.07 %   | 65.20 %   |

Quantitative analysis
For a quantitative evaluation of the ability of slant-range PanTex to discriminate between BU and NBU areas, a different reference set was used. Specifically, eight selected areas of 1 x 1 square km, four in the central portion of Nairobi and four in the urban fringe area for a total of 4.25% of the classified area. For these test areas BU maps were obtained from visual interpretation of VHR optical data at 1 m spatial resolution, and then resampled to the spatial resolution of the SAR data. BU and NBU classes are equally represented in the test areas (49% against 51%).

Overall accuracy for each test area was computed, whose mean value provide information on the ability of the index to depict real buildings in urban areas against different land covers. The results in Table 3 show the general trend toward increasing accuracy for wider windows used for the computation of the index which apparently reaches a maximum for a width between 100 and 200 m, due to a better discrimination in the urban-rural fringe. This effect compensates for the decrease in accuracy in the central city area for the larger window width, too large for that environment.

Table 3 - Mean values of slant range PanTex evaluation for BU against NBU discrimination.

| Data set | w= 50 m | w = 100 m | w = 200 m |
|----------|---------|-----------|-----------|
| F2D      | 76.64 % | 77.58 %   | 77.64 %   |
| F5D      | 67.33 % | 83.88 %   | 67.52 %   |
| ALOS     | 77.64 % | 78.36 %   | 77.78 %   |

Comments on the results
There are some general observations driven by the results in the previous section, as well as some specific comments on the two different areas. First of all, it is easy to observe that the slant-range index is generally capable of discriminating between built up areas and their surroundings. The new definition of the index provides for SAR data values with strong correlation to the actual built-up areas, except for the areas where the viewing angle of the SAR sensor makes this latter unable to receive high backscatter values from man-made targets because of the relative positions between these objects and the sensor. In this situation, combination of more SAR data is likely to reduce the problem [Dell’Acqua et al.,
2003], and especially the use of both ascending and descending passes is recommended as the most powerful way to avoid or at least reduce the cardinal effect. More specific comments on viewing angle conditions, but still independent from structural characteristics of the built-up area, can be derived by comparing the F2d and F5d results on the test sites at the optimal resolution conditions. With respect to this point, we may observe that the accuracy values are not significantly different, as they all hinge around 80%.

With respect to effects associated with different frequencies, the comparison between RADARSAT-1 and ALOS PALSAR data did not provide evidence of one frequency being clearly superior to the other. The results are more dependent on differences in viewing angle and orbit direction than on frequency differences. The effects observed in the L-band derived index over areas with mixed vegetation, however, suggest to give preference to the higher frequency of the C-band. Indeed, a look at Figure 5 shows that the index computed starting from PALSAR data has a lower contrast between the settlements (the Kibera slum in Nairobi Central District) and the golf course North of it.

Figure 5 - A visual comparison of the (a) ALOS original data set, (b) F2D “ground-range” and (c) F2D “slant-range” PanTex for a computational window of 21x19 pixels of the Kibera slum, close to Nairobi Central District (d).
From the processing point of view, the window width most useful for generating the index from SAR data is apparently between 100 and 200 m. This marks a further difference with respect to optical imagery with similar spatial resolution. The optimal GLCM window size to be used for delineating built-up areas consisting of standard size buildings was determined to be 9 x 9 pixels in case of imagery with a spatial resolution of 5 m [Pesaresi et al., 2007]. While spatial posting of the RADARSAT-1 Fine Beam data is quite similar, being 4.63 x 5.29 m in the original slant-range geometry, the analysis of the sample scenes shows that the best window width depends on the test area, but basically with the larger ones generally being superior. In fact, they still retain interesting information and smooth out much of the speckle noise, making the final result more understandable. Moreover, they fix the problem of sparse co-occurrence matrices when 256 gray levels and only 9 by 9 pairs are considered.

Conclusions
This work has shown that the anisotropic rotation-invariant built-up presence index, originally developed to detect built-up area in optical images, can be successfully extended to SAR data. The new slant-range formulation of the index is suitable for detection of small building clusters, and fully exploits the spatial and radiometric resolution of the original data. The optimum GLCM window size to be used for the index computation is expected to vary with spatial resolution of the data, but large window sizes are preferred. Apart from this fine-tuning, our experience is that windows in the range of 100 m are usually the best choice. The value of the introduced built-up presence calculation is only exploited fully in its representation as a “fuzzy” gray-level index with increasing values representing a growing membership of the pixel to the class built-up. Values then range from 0 corresponding to “no buildings” to 255 representing “high density built-up area.” Ongoing research will explore in more detail the correlation of the index values with building density and land use for urbanized areas in different parts of the world. The objective is to develop procedures to fully exploit the index for improving global settlement and population maps.

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