GIS-AIDED PER-SEGMENT SCENE ANALYSIS OF MULTI-TEMPORAL SPACEBORNE SAR SERIES WITH APPLICATION TO URBAN AREAS

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Abstract— It is well known that multi-temporal series of SAR data are able to provide interesting clues about temporal evolution of some land covers. In this work, a per-segment approach based on the use of ancillary Geographic Information System data is proposed. Two test cases show the effectiveness of the technique and its usefulness for quickly detecting changes in urban areas and discriminating to some extent different urban dynamics.

1 INTRODUCTION

The availability of long time series of SAR data is a very interesting effect of the long and successful missions carried out by national and international space agencies. ERS-1 and ERS-2 has been providing a consistent data set of observation of the earth surface since 1992, when the first of these two satellites was launched. Similar time series are available from the Canadian RADARSAT-1 or from Japanese JERS-1 archives. For each of these missions, future coverage is secured by follow-on missions: ENVISAT-1 and Sentinel-1 for ESA, RADARSAT-2 for the Canadian Space Agency, ALOS for JAXA. Moreover, since past and to some extent future data are not the result of systematic acquisitions, JAXA has devised (Rosenqvist *et al*. (2007)), a background mission for the PALSAR sensor, meant to overcome this shortcoming.

Still, the data already in the archives is a huge collection of information which has been underexploited so far. This research work is meant to evaluate other means to use these data, focusing on a specific environment, i.e. urban areas, and a specific problem, i.e. change detection and image mining.

The definition of a long ``multi-temporal'' SAR data series is basically ``a set of scenes of the same area observed by the same SAR sensor on the same track with the same viewing angle". Given the configuration of the ERS missions, and the fact that both satellites were placed on the same orbit and carried the same radar sensor, the same portion of the earth surface was possibly imaged every 35 days since 1992. A quick search in ESA archives shows, for instance, that 11 images were collected by ERS-1 covering the town of Pavia in northern Italy from tracks in an ascending orbit. Additionally, 32 images were collected by ERS-2, and 30 more by ENVISAT-1 so far. Summing up, there are 73 images available (and many more considering descending passes) that covers from July 1992 to July 2008, with time lags generally in the range between 24 hours and 35 days, except a few longer gaps.

Similarly, the entire African continent has been fully covered every one or two months by the ERS missions, which means that radar measurements, thanks to their all-weather and night-and-day capabilities, offer a continuous record of observations increasingly important for regional and/or global models requiring graphically dense inputs available from radar data.

Indeed, many important applications of these long series of data have been already designed, the most famous being Differential SAR Interferometry (Colesanti *et al*. (2003), widely used for subsidence monitoring (Ferretti *et al*. (2000), Berardino *et al*. (2002)) and, more generally, for monitoring changes in terrain/structure heights with a rather long temporal scale. Similarly, SAR data series have been used for the analysis of long-term behavior of urban areas by means of interferometric coherence (Usai (2000)). These applications fully exploited the spatial resolution of the data. They refer also to natural phenomena with rather long temporal scale, well captured by the long while often discontinuous temporal sampling of the available spaceborne SAR data series.

Other applications, too, such as forest mapping (Quegan *et al*. (2000)) and rice monitoring (Kurosu *et al*. (1995), Le Toan *et al*. (1997)), have proved themselves feasible, because the SAR data temporal sampling is adequate to capture the temporal behavior of vegetation species. Little or no attempt was done, however, in all these applications to exploit the spatial content of SAR images. Fewer attempts were made to analyze temporal changes in spatial patterns. Most recent techniques in signal processing (notably, wavelet decomposition) have shown that different combinations of spatial and temporal scales exist that are capable of characterizing a signal (in this research a natural phenomenon). For instance, to complement the already mentioned long-term analysis at the pixel level of urban areas, block-level change detection has proved to be effective for quick damage assessment after natural disasters (Gamba *et al*. (2007), Gamba and Trianni (2008)).

As a matter of fact, there is no general scheme and analysis in technical literature designed to track different land covers using long multitemporal SAR sequences. Reason is that the spatial scale of each land cover is different, and the temporal behavior is different as well. Multitemporal change detection between two dates has been widely analyzed at the segment level (Pagot *et al*. (2007), Pesaresi *et al*. (2007)), but long multitemporal per segment analysis is a rather new research subject. In principle, the problem may be approached by using a suitable segmentation of the scene at each date followed by a complex tracking mechanism, like in tracking applications (Nastar and Ayache (1996)). SAR scene segmentation is however a very complex task, and even the most effective approaches (Oliver and Quegan (1998)) have not been tested on long sequences. They are also very dependent on scale parameters connected to the statistical properties of the segments. In the experience of the authors (Macri Pellizzeri *et al*. (2003)) it is difficult, especially in inhomogeneous scenes, to find a unique set of parameters. Some sets will result in oversegmentation in some portions of the scene and other ones in undersegmentation of other parts. Multiple segmentations and thus multi-scale tracking would be required.

This research line, while extremely interesting, is not directly suitable for quick multitemporal sequence data mining, for instance looking for sequences with a specific land cover change temporal patterns. A simpler way to focus the attention of the analysis to the right scale for each land cover is required. To this aim, this work is devoted to the analysis of long temporal series of intensity ground range SAR data using Geographic Information System (GIS) data. Where GIS data are available, a per-segment analysis might be easily performed. In many situations this is exactly what is available for most man-made features and for parcel boundaries, both within and outside urban areas. Just to give an example, Corine Land Cover (CLC) data, ubiquitous all over Europe, is freely available and could be used as a time stamp of a consistent segmentation, at least at a regional or national level, of European land covers, according to its scale (1:100,000).

The methodology to extract spatial information from long temporal SAR series using GIS data will be introduced in next section, and results for two test cases will be presented in Section III. The focus will be on urban areas and thus on urban change detection, but the approach may be adapted to different situations and it could be explored for other environments as well, as pointed out in the conclusions.

2. MULTI-TEMPORAL SAR SERIES AND LAND COVER MAPPING

Let us assume that an hyper-temporal data series X_n is available, with $n \in \{1, \cdots, N\}, N \gg 1$. The simplest approach that could be taken with these data is the same as per multi-spectral images, where $X_n(i, j)$ has no longer the meaning of a ``spectral" response, but it is now the ``temporal" response of the ground area imaged in the $(i, j) - th$ pixel of the area. Unlike multi-spectral images, however, where the bands are acquired simultaneously, here the spatial alignment of the pixels belonging to each temporal band to the previous and the following bands is not guaranteed. Luckily, this problem has been already studied, as for SAR data is concerned, for differential interferometric applications (Sansosti *et al*. (2006).

A second, well-known problem in SAR images is speckle noise; in a per-segment approach, though, despeckling is a less critical step, since recovery of the information hidden by speckle noise is entrusted to the spatial analysis. As a matter of fact, joint segmentation and despeckling have been already proposed and efficiently implemented (Oliver and Quegan (1998)). In a GIS-aided segmentation, however, segments are not related to the statistical properties of backscattered SAR signal, since they are independently obtained (often from interpretation of optical data). A general speckle-removing routine is thus a natural option to reduce speckle effects. For a long temporal sequence, the most suitable choice is a multitemporal algorithm (Gamba and Trianni 2008). While the optimal approach would require to compute the complex correlation between any pair of images to achieve the largest possible improvement in the Equivalent Number of Looks (ENL), the simplified assumption that each image is uncorrelated to the previous one allows using the simplified form

$$J_k\left(x,y\right)=\sigma_k\,\frac{1}{N}\sum_{i=1}^{N}\frac{X_i\left(x,y\right)}{\sigma_i} \tag{1}$$

where J_k is the filtered version of the k-th original image X_k, and σ_k and σ_i are the intensity mean values, estimated in a MXM neighborhood of the current (x,y) position (M to be defined as a function of spatial sampling of the data).

As noted in (Quegan and Yu (2001)), the assumption is invalid in urban areas, where coherence is high over long time periods (Usai (2000)). This means -naturally- that the suboptimal approach will not achieve the predicted improvement in these areas; it does however contribute to cleaning up the data, and still performs satisfactorily on non-urban areas, relevant in our case to e.g. land cover change analysis. Many works on multi-temporal analysis of urban areas using SAR (Macri Pellizzeri *et al*. (2003), Gamba and Dell'Acqua (2006)) confirm that per-pixel analyses in these environments for classification purposes show very poor performances notwithstanding speckle filtering.

After speckle noise reduction, the following step of the procedure, schematically depicted in fig. 1, is GIS-aided segmentation. This basically results into substituting pixel values with segment values for any of the bands in the multitemporal sequence. Let us use the same notation as in previous equations and let us define s as the generic segment inside the set S obtained via the GIS data. Then, the analogue to equ.~(1) would be

$$J_k^s\left(x,y\right)=\frac{1}{N_s}\sum_{(x,y)\in s}F\left(X_k\left(x,y\right)\right) \tag{2}$$

where F( ) stands for a generic operator, and N_s is the number of pixels belonging to segment s.

Assuming F( ) as the log( ) operator, the spatial analysis would result in the effect of fig. 2(b) for the same sample area in fig. 2(a). In a more general way, and in order to preserve the richness of the original data within any segment, the operator *F*( ) might be chosen to be one or the combination of more measures of the textural information pertaining to each segment.

The more general choice, however, is the variance (or standard deviation) of the intensity values. More complex features, e.g. co-occurrence texture measures, would be too peculiar to one or another of the land covers which underlies the GIS segments, and would make the procedure too class-specific. The variance is instead a basic statistical quality of the data belonging to a segment, and thus it may be used to extract information which is related to other parameters of any model best fitting the land cover (urban, agricultural, forested or other) of the spatial segment under test.

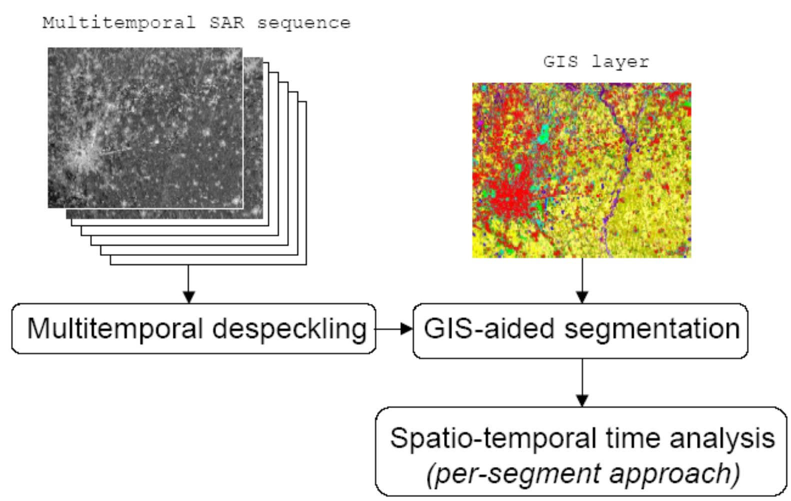

Fig.1: Overall structure of the per-segment approach to the analysis of multi-temporal SAR sequences.

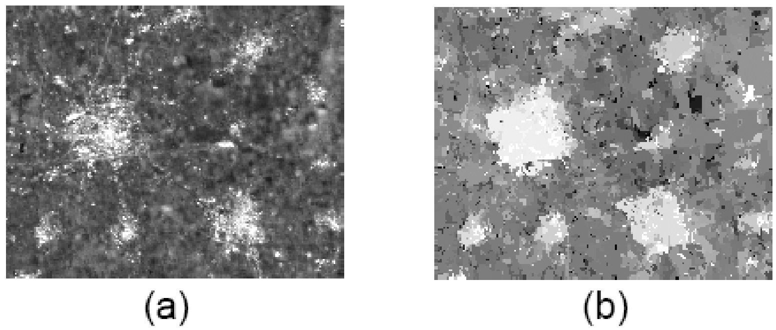

Fig.2: Subsample of (a) original SAR intensity data and (b) the corresponding GIS-aided segmentation result (Logarithmic mean values of backscattered intensity are assigned to each segment).

As stated in the introduction, the significance of such statistic measures on every segment would be best if the boundaries were extracted in accordance to some consistent segmentation procedure based on the SAR data itself. However, in this work the boundary information is obtained from a GIS layer which represents instead a totally independent source. This replacement, essential to apply a meaningful segmentation to the multitemporal scene, in fact makes the choice of representative parameters less critical. As a consequence, since the mean and the standard deviation of the intensity values are well-known and robust indexes (Oliver and Quegan (1998)) for SAR data in a homogeneous segment, in the following we will focus on these.

3. EXPERIMENTAL RESULTS AND APPLICATIONS TO URBAN AREAS

The data sets used in this project refer to two different test areas, both in the North of Italy, and to two different situations. The first set is composed by a comparatively short temporal SAR data sequence, manually co-registered in a small area of interest. The second one is instead a much longer SAR sequence on a wider area, obtained as a side result of long-term differential interferometric processing.

The first test set is made of ERS-1 and ERS-2 images over an area of the Lombardy region in Northern Italy, centered around the city of Pavia. They were acquired on the following dates:

- August 13th, 1992 (ERS-1),
- October 22nd, 1992 (ERS-1),
- June 24th, 1993 (ERS-1),
- November 21st, 1993 (ERS-1),
- October 3rd, 1994 (ERS-1),

- November 9th, 1994 (ERS-1),
- July 22nd, 1995 (ERS-1),
- October 29th, 2000 (ERS-2).

The original SAR images were collected to study the effects of the 1992, 1993, 1994 and 2000 floods of the Ticino river, flowing South of Pavia (Dell'Acqua *et al*. (2004)). After a precise manual co-registration, the multitemporal sequence was elaborated by using a GIS layer, extracted from the above mentioned Corine Land Cover and referring to year 1990. The boundaries of the segments in that layer belonging to the urban land cover classes are represented in fig. 3(a), and were used, together with those belonging to other classes, as input to the segmentation of the SAR data series. For each segment, as exemplified again for some urban areas in fig. 3, the computed statistical values form ``time trajectories'' able to provide condensed yet useful information.

Of course, due to the temporal sparsity and short duration of the sequence, the spatio-temporal analysis of the these time trajectories is relevant for areas whose statistical properties are likely to be stable or underwent changes in the considered time frame: For this reason, the most useful set of segment to look at is again those belonging to human settlements. Fig. 3(b,c) show time trajectories for the logarithmic mean and variance of their intensity values, respectively. To make the analysis more significant, in the largest towns more segments were considered, while small cities were analyzed as a whole.

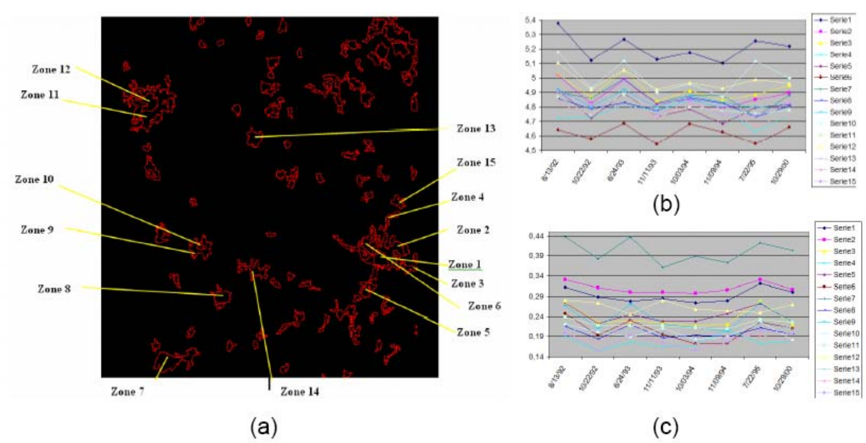

Fig.3: The extents of human settlements extracted from the Corine Land Cover for the area covered by the first SAR multitemporal data set (a), and temporal trends of logarithmic mean (b) and variance (c) values for a few segments.

The graphs show that of the logarithmic mean values are higher for the homogeneous areas, namely, the centers of the cities. For example, zone 1 refers to the city center of Pavia, the biggest town in the area, and the temporal trend for this zone shows that it has always the highest backscattered field values in the area. We can also notice that almost all of the areas show a regular temporal trend, even considering variance values. The sudden changes for some of these areas correspond to the above mentioned flood events (Dell'Acqua *et al*. (2004)). Since some parts of Pavia and other settlements along the Ticino river were flooded, the presence of water temporarily changed the backscattering properties of the corresponding segments.

This first test shows therefore that there is some interest in working on temporal patterns of SAR intensity focused by means of GIS land cover layers. It may be expected that the analysis of a longer image sequence may result in more discriminating power among different land cover classes.

To prove the point, a second data set was considered. It is a long, multi-temporal intensity SAR sequence, made out of overlapping portions from 73 ERS-1 or ERS-2 scenes, recorded between years 1992 to 2000. This temporal sequence is also oddly spaced, and time lags as short as 1 day or as long as one year are both found. Since there is no real need to know each date of acquisition, they are not reported here. It suffices here to say that all the images are precisely co-registered, as a side product of differential interferometric processing. The available data portion refers to a geographic area located in the North of Italy, spanning between the two cities of Milano and Bergamo, located at its Western and Eastern extremes, respectively. The area is a rapid changing one, in terms of land cover and land use, with impervious surfaces quickly expanding at the expense of arable land.

Knowledge about the area is again available through a Geographical Information System (GIS) data provided for the whole Lombardy region by the Regional Agency for Environmental Protection (ARPA Lombardia). These GIS layers are available for two dates, year 1999 and 2004, and are the result of the continuous monitoring efforts by the regional environmental authorities, in order to control the territory. They were obtained by manual photointerpretation of diverse remote sensing data sources, namely aerial campaigns and spaceborne VHR optical imagery. The land cover legend used in these layers is very detailed (19 classes), but was reduced to 5 basic classes (urban areas, water bodies, urban vegetation, seasonal vegetation, other vegetation) for this research work.

By combining the multi-temporal SAR sequence and the GIS land cover map, a per-segment analysis can be easily performed, producing time trajectories. As note above these trajectories describe changes in backscattered electromagnetic intensity. Thanks to the above mentioned temporal despeckling filter, these trajectories should not be affected by data noise to an unacceptable extent. However, in order to take into account effects by full-developed speckled that may not be completely cancelled by the previous processing steps, this work is based just on the comparison among temporal patterns of different segments. In other words, we do not trust completely the data, but assume that remaining speckle effects at one date will equally affect all segments.

First of all, fig.~4 propose different trajectories for ``stable'' segments, i.e.~segments that did not undergo any change in their land cover during this period. They were selected by means of the available GIS layers. The graphs in fig. 4(a,b) depict logarithmic mean and the standard deviation for the full SAR sequence.

- Urban areas (in red) show the largest values for both the indexes, but also a negligible change over time. This is consistent with the strong backscattering effects in urban areas, dominated by double bounces between the ground surface and the building walls. The high variability of the urban landscape would have suggested a large variance, but the coarse resolution of the data and the ground range projection mask this effect, providing a surprisingly low value, and moreover stable along time.
- Water bodies (in blue) are less stable in their temporal behavior, because of Bragg scattering due to wind conditions, but with lower mean values, due to their specular scattering effect in the microwave region.
- Vegetated areas (in green) feature an intermediate behavior, in terms of index range, but also with a wide interannual variability.

It is apparent that the study of these trajectories provides insights about some of the physical properties of the land surface in areas belonging to the same land cover class. This allows a better characterization of each segment or, in case, a quick check of the consistency of the backscattering temporal behavior with the class to which the segment is known to belong to.

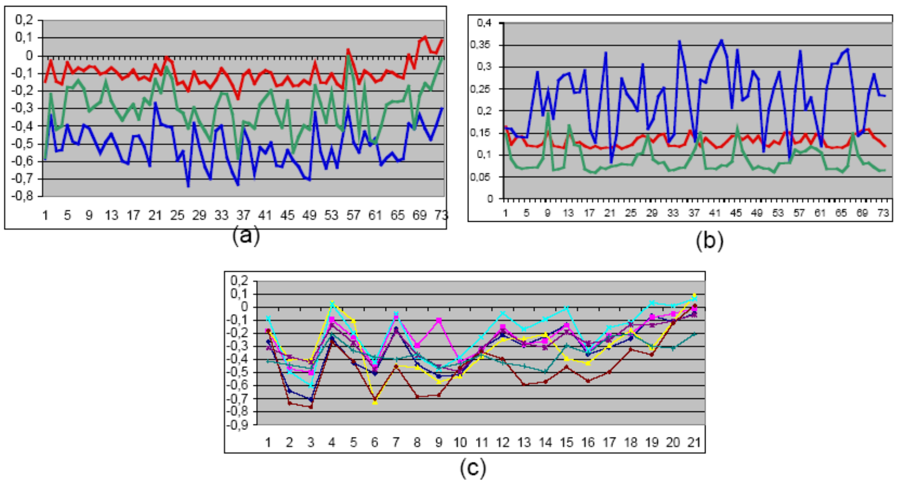

Fig.4: Some of the time trajectories for segments belonging to different land cover classes for mean (a) and variance (b) of the logarithmic intensity values (color legend is provided in the text), (c) time trajectories for the mean of the logarithmic intensity value of areas subject to change towards the ``urban'' land cover class between 1999 and 2004.

Some complementary -and maybe more interesting- analyses can also be carried out. One of these is quick change analysis in urban areas. According to what discussed above, urban areas undergoing changes in the time period spanned by the multi-temporal series should be detected by looking to urban areas in 2004 with a time pattern that does not fit the above highlighted patterns. In the specific case, the approach should be able to detect by means of this ``backward analysis'' the areas which changed from rural to urban (or from low to high-density urban, or any other change).

This idea is confirmed by looking at time trajectories of areas labelled as ``urban'' only in the 2004 map, shown in fig. 4(c). Please note that in that graph only 21 images are considered, referring to the time frame between 1999 and 2000, the only portion of our ERS multi-temporal sequence that overlaps with the changes available from GIS maps. A visual analysis of these time trajectories shows that they are different from those of stable urban segments in fig. 4(a). A more detailed analysis allows extrapolating that changes took place at different dates. In fact, while the patterns are similar, there are significant differences in the location and shape of the slope change.

The above-introduced time trajectories could be considered as the temporal signature of each spatial element in the scene, and studied accordingly. Similarly to spectral signatures of objects in multispectral images, these temporal signatures in multi-temporal SAR sequences could be manipulated for image mining and ``temporal unmixing'', with a procedure parallel to spectral unmixing in multiband data. Like multiband optical data are used to estimate the vegetation surface fraction (Schmid *et al.* (2005)), we could use hyper-temporal time trajectories to estimate ``change fractions'', i.e. to evaluate the similarity of each of the segment to a known change pattern.

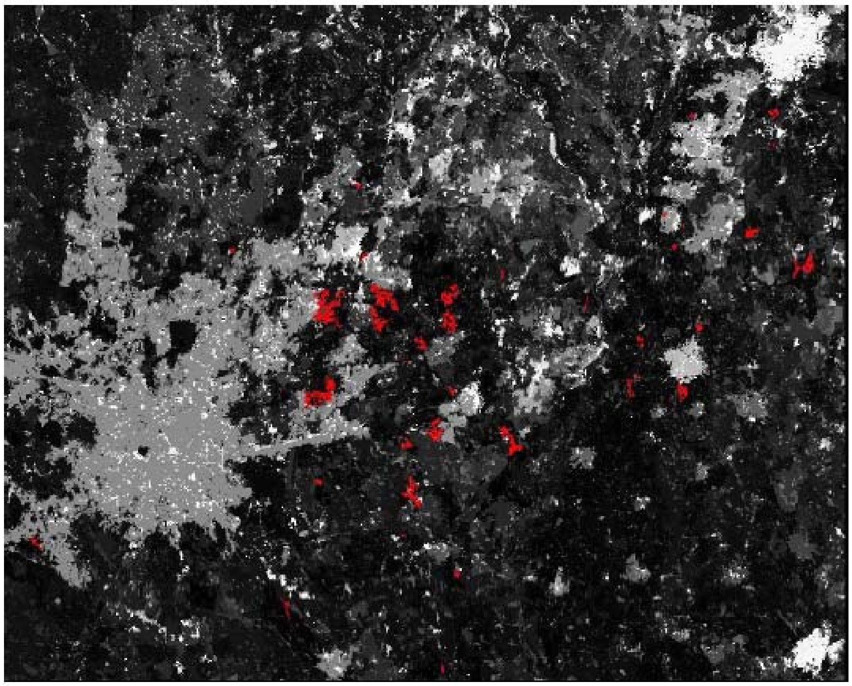

Fig.5:``Temporal unmixing'' of time trajectories looking for changes from rural to urban land cover class in the 1999-2000 time frame.

Just to give here an example, we assume we know the temporal pattern referring to an area that changed from arable to urbanized land between 1999 and 2000. This known time trajectory (one of those in fig. 4) is used as input to a well-known algorithm for similarity checking in multi-spectral and hyperspectral signatures, the Spectral Angle Mapper (SAM) classifier. Results are shown in fig. 5, where the red color highlights the most similar temporal behavior to the known one. In the background, the image shows the similarity of each segment, with lighter grey levels meaning lower similarity values. Validation of these segments have been carried out using the GIS maps, showing good agreement.

4. CONCLUSIONS

This paper shows that interesting information about land cover temporal patterns may be extracted from multi-temporal SAR sequences provided GIS data of the same area is available. GIS is able to solve the problem of scale which make date-by-date segmentation and segment tracking a highly complex task for SAR data.

On the contrary, by substituting the data-driven segmentation with a GIS-aided focusing on the segments available in available data layers, it may be possible to track the temporal behavior of land cover segments without the need of a date-by-date, error-prone classification. We stress the fact that, depending on the temporal samples in the sequence, the time trajectories may or may not be able to capture temporal features of a specific land cover. For urban area applications, given that urban areas usually undergo slow changes in time, long unequally sampled multi-temporal sequence are still useful.

Therefore, we have shown that this approach can be exploited for quick identification of temporal trajectories of human settlements and to some extent detect when a specific area underwent a change. Moreover, it can be used for a fairly easy mining of the temporal SAR intensity sequences, already available in on-line archives. By looking for temporal patterns similar to a known sample, e.g.~a known urban change pattern, similar patterns can be located and areas of interest extracted with their temporal behavior.

So far, the crucial point of the procedure is the availability of an independent segmentation of the area, coherent with the actual boundaries between different land covers. A need thus emerges to better link the two sources of information (the radar backscattered values and the GIS layers), and this is going to be one of the leading pathways of the research on this subject in the future. In turn, this would require an investigation about different statistical (and presumably textural) features of the SAR images to be considered for data interpretation in the per-segment approach.

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