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Towards Detection of Archaeological Objects in High-Resolution Remotely Sensed Images: the Silvretta Case Study

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Abstract:
We report on recent research undertaken in the framework of the Silvretta Archaeological Project, in which we are developing methods to detect certain types of archaeological ruins in remotely sensed images in order to assist archaeological survey. Our approach aims at assessing the probability of the presence of objects of our interest based on geometric cues that can be automatically detected in the satellite and aerial images that we use. We describe our methodology and the first integral step, constituting a new approach to texture segmentation that we developed to reduce the rate of false detections.

Keywords:
Archaeological Survey, Remote Sensing, Texture Segmentation, Texture Contrast

1. Introduction

In his keynote lecture during the opening session of the Southampton CAA conference, Jeremy Huggett identified digital image analysis as one of the great challenges of digital archaeology for the next few years (Huggett, this volume). We agree because the amount, variety, and availability of digital images as well as their actual or potential use in archaeology, has increased dramatically since the introduction of digital optical sensors in earth observation remote sensing in the 1970s (Giardino 2011). With regard to image analysis, it seems however that archaeology lags behind other disciplines (De Laet and Lambers 2009, Lasaponara and Masini 2012, Cowley 2012). For example, in such diverse fields as earth observation, surveillance, transportation, medical imaging and social media, digital image analysis is today not only used routinely to correct or enhance images, but also to analyse their content, which often includes object detection using computer vision approaches. Automated visual analysis has substantially advanced in recent years, now allowing for a variety of targets to be automatically detected, such as buildings, roads, people, or various patterns in medical images. Moreover, remarkably successful algorithms and technologies have been developed for face detection and for object detection for autonomous car navigation (Szeliski 2010). In spite of remaining limitations, these examples demonstrate the potential of automated object detection across different disciplines.

In contrast to the aforementioned sciences, in archaeology, the interpretation of remotely sensed images, including the detection of archaeological sites and objects, is in most cases still the domain of archaeologists visually inspecting and interpreting the images. Just a few recent studies go beyond that level by attempting to correlate spectral image properties and archaeological site distribution (e.g., Beck et al. 2007, Menze et al. 2007, Garrison et al. 2008, De Laet et al. 2009, Evans and Traviglia 2012). The generally rather conservative approach reflects the notion that the intrinsic variety of the archaeological record will make failure of computer-based object detection likely (see review of current debate in Cowley 2012).

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***Figure 1**. The Silvretta region in the central Alps (red box) and the partner universities involved in the project (Bamberg is outside the map).*

While this objection may appear plausible at first glance, it often seems to be based on the misunderstanding that an automated object detection approach aims at a complete register of all archaeological sites and objects of a given region, potentially replacing visual image interpretation and/or fieldwork by archaeologists. This cannot be the goal of such an approach. Human vision is clearly superior to the current state of computer vision, and will remain so in the near future. In fact, all the above-mentioned cases of successfully applied object detection across various disciplines target only well-defined categories of objects. This is also true for the few but inspiring archaeological case studies in this field (e.g., Trier et al. 2009, Trier and Pilo 2012).

While expert knowledge and fieldwork will remain indispensable for any serious archaeological research, automated algorithms may well be used to assist with routine and time-consuming tasks. A typical example is regional archaeological survey, especially when undertaken in vast, difficult, and/or hitherto unexplored terrain. In such cases aerial or satellite images are often visually inspected prior to fieldwork with the goal to identify potential sites and typical site categories to guide fieldwork. Automated screening of large image data sets may offer valuable assistance and increase work efficiency in this case. The results would guide and enrich fieldwork rather than supersede or constrain it.

2. The Silvretta Archaeological Project

To develop methods as outlined above, one needs to start from a sample of documented sites in a region covered by remotely sensed images, as is the case in the Silvretta mountain range on the Swiss-Austrian border (Fig. 1). An ongoing research project in this area (Reitmaier ed. 2012) is currently serving as a case study to explore the potential of using object detection on remotely sensed images to assist archaeological survey.

Archaeological fieldwork in the Silvretta region was initiated in 2007 by Thomas Reitmaier, then at the University of Zurich, with a focus on the human occupation of the region during the Bronze and Iron Age. An important goal was to investigate the origins of alpine pastoralism, or *Alpwirtschaft,* an economic system of resource use highly adapted to the challenging environmental conditions in the high mountains (Reitmaier 2010, Gleirscher 2010). With the incorporation of project partners from the universities of Innsbruck, Konstanz, and Bamberg, and from such diverse disciplines as paleoecology, geography, geology, linguistics, and computer science, research in the Silvretta region has since grown into an international and interdisciplinary project. It addresses among other topics, Holocene landscape genesis and settlement history, human-environment interaction, and questions of cultural continuity in the high mountains (Reitmaier ed. 2012, Walser and Lambers 2012). Within this broad framework, the earliest indications of human impact on the landscape, and the transition from hunting to herding, defining the origins of alpine pastoralism, remain key research questions.

The permanent basis of alpine pastoralism is the settlements of farmers in the lower valleys, where livestock is kept in stables during the winter. As snow-covered areas recede in spring, livestock is driven uphill to pastures on the valley slopes and finally, during the short summer, onto fertile pastures above

***Figure 2**. Ruins of alpine huts in the upper part of the Fimba Valley, Switzerland (photos: K. Lambers, T. Reitmaier).*

the tree line, i.e. areas otherwise unsuitable for permanent occupation. In archaeological terms, alpine pastoralism is associated with built infrastructure that can still be observed in our study area today, like huts and cabins for seasonal dwelling, enclosures to protect livestock from wild animals, and, if dairy farming was involved, cheese cellars with access to water. Many of such architectural remains have been documented in the Silvretta region (Fig. 2). While the harsh environmental conditions have caused substantial damage to some sites, most are still visible on the surface since destruction by modern land use is minimal.

3. Project Goals

While being unique in their specific forms, the above-mentioned sites and buildings show a limited variability of geometric properties in their shapes and proportions. They thus constitute a typical problem of object detection, in which the task is to detect structures of similar shape. In order to develop a general approach of archaeological object detection, we decided to use the registered sites associated with alpine pastoralism, among them approximately 20 well recognizable ruins, as starting point. Corresponding to their function and purpose, all of these sites are located in open grassland, most of them in the alpine zone above the tree line (Fig. 2). We therefore defined open grassland as our region of interest.

Other categories of archaeological sites also registered during our survey, such as fireplaces and rock shelters, are not considered in this approach. Furthermore, we do not currently pursue other potential approaches we discussed prior to image acquisition to identify archaeological sites (Lambers and Reitmaier 2013). Our goal is to develop a method that assesses the probability of the presence of archaeological objects of the type described above in a given area based on their geometric properties. The expected result is a probability map of candidate sites in our study area that can be visually verified prior to fieldwork. The quality of such a map will be judged by its sensitivity to structures resembling objects of our interest and the rate of false detections. A low rate of false detections in various terrains is essential for our methodology to be useful, which means that segmentation of high contrast textured regions as described below is crucial.

It should be noted that our ultimate goal, the detection of archaeological structures in vast unknown areas, differs essentially from contrast enhancement and automated mapping of known sites and structures as undertaken in other archaeological projects (e.g., Jahjah and Ulivieri 2010).

4. Image Data

We decided to use high-resolution satellite images for image data. Although our study area is covered by various sets of aerial images, none of these is available for the whole study area because the study area is divided between two Austrian federal states and one Swiss canton. Furthermore, in mountainous regions aerial images suffer from distortion caused by greatly varying terrain elevation. Satellite images, on the other hand, are able to cover the whole study area with consistent, up-to-date images and are less distorted due to the much greater distance between camera and terrain surface.

Another more general reason led us to choose also satellite images. We believe that satellite images with a high spatial resolution of 1m and better will prove an important data source for archaeology in the future (Parcak 2009, Giardino 2011, Lasaponara and Masini 2012). Since this kind of imagery first became available in 2000, its quality and variety has increased dramatically. Today, nearly worldwide no other high-resolution image data source is available under consistent conditions and without major legal constraints. High-resolution satellite images are therefore likely to become the preferred data source for regional archaeological research in many areas of the world where alternative data sources, such as aerial images, are not easily available.

For the Silvretta project, we chose to order GeoEye-1 images. The camera mounted on this satellite launched in 2008, captures images featuring a panchromatic channel and four colour channels (RGB + NIR) with a spatial resolution of 0.41m (pan) and 1.64m (VNIR), respectively. We ordered the bundle product comprising the panchromatic channel and pansharpened colour channels. Due to legal regulations, after pansharpening all channels were downsampled to a spatial resolution of 0.5m pixel size. While lower than that of most aerial images, this spatial resolution still allows the detection of structures pertaining to our target objects. The characteristic size of the archaeological ruins we are looking for varies roughly between 10 and 100 pixels. Their walls are generally not wider than two pixels. Reliable detection of structures of a few pixels in width is very limited. In some cases it might not be achievable at all. However, in our case the second dimension of walls, whose length is usually above 10 pixels, makes this task still possible.

For improved georeferencing and orthorectification of the GeoEye-1 images, we provided ground control points measured by graduate students of geomatics at ETH Zurich during their summer field course in June 2011. Furthermore, we ordered images with a cloud cover of less than 5%, which is important in the Alps where weather conditions are volatile. After a rainy summer, four scenes of our study area where finally captured on September 6, 2011. Following image processing by GeoEye, we received the image portions that cover our study area of approx. 540 sq. km in early November 2011. By that time, we had already started to develop first elements of our method on Swisstopo orthoimages with the same resolution of 0.5 m to expedite the start. These elements were applicable to the satellite images, too. All further research was conducted on the GeoEye images.

5. Digital Image Analysis: General Methodology

Our method aims at capturing geometrical properties of the objects of our interest mentioned above, namely ruins of livestock enclosures and alpine huts. Such structures can be modeled by linear features that meet at approximately right angles.

Our general methodology is divided into several stages that extract image features of growing size and complexity. In the first stage, local features such as black and white blobs stemming from the background are extracted from the image. This stage can be implemented by means of white or black top-hat transforms (Soille 2003) or their combinations. Colour information can also be incorporated into these transformations, as suggested by Hanbury

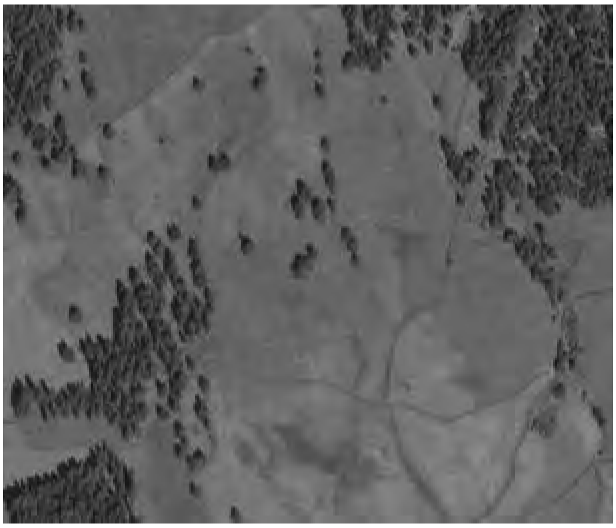

***Figure 3**. A patch (1360x1160 pixels) of an image taken from the upper left part of Fig. 6(a).*

(2004). While we currently do not use colour information, this could be beneficial in cases where colour contrast is higher at the image features we are interested in.

Chains of blob features with possible gaps in between may form linear features. During the second stage, we group extracted blobs into larger, approximately linear features that may correspond to the walls of ruins of huts and enclosures. Near right angle intersections of linear features that may be defined by corner points, are then searched in the next stage. Although many approaches for line and corner detection exist, they are not robust enough to be widely applied to different types of images with different scenery, textures, irrelevant structures, noise, illumination conditions, and contrasts. We are currently investigating these topics, aiming at the development of new line/corner detection algorithms adjusted to our specific task and the type of imagery we use.

Evidence of structures of interest can then be inferred from extracted linear features, corners, and contextual keys, if available, for instance surrounding texture. This is the final stage of our methodology to be developed in the future. The output of the last stage is a probability map indicating the presence of objects of interest. Such a map will have zero values at most regions, and a continuous range of probability values at other regions. This map can be further thresholded at the level corresponding to an acceptable rate of false detections.

Our database that includes about 20 objects of our interest is rather limited when taking into account the variations in the appearance of the objects. It thus does not allow us to employ machine-learning techniques. It nevertheless allows us to develop approaches based on geometrical properties and other known key features. It also allows for a coarse estimation of the achieved sensitivity. Since we acquired a large amount of satellite images, we can reliably test the corresponding rate of false detections.

For our general approach to succeed, it is essential to discriminate between smooth and high contrast texture regions in our images. For this basic prerequisite, we developed a new method described below.

6. Texture Detection

While the concept of texture has no precise definition, it is generally associated with repeated changes in image grey level. In remotely sensed images such as the ones we use in the Silvretta region, high contrast textures are, for example, forests (Fig. 3) or urban areas. Large amounts of local features are usually extracted in texture areas in the first stage of the described methodology. This is because the local operator does not distinguish isolated features like blobs or lines from features that belong to a different context, a texture. Grouping at the following stages does not suppress these features since they are easily grouped with other surrounding texture features resulting in unexpected false detections.

To overcome this problem in areas such as forests, urban areas, or rocky mountains, we developed a new texture detector that

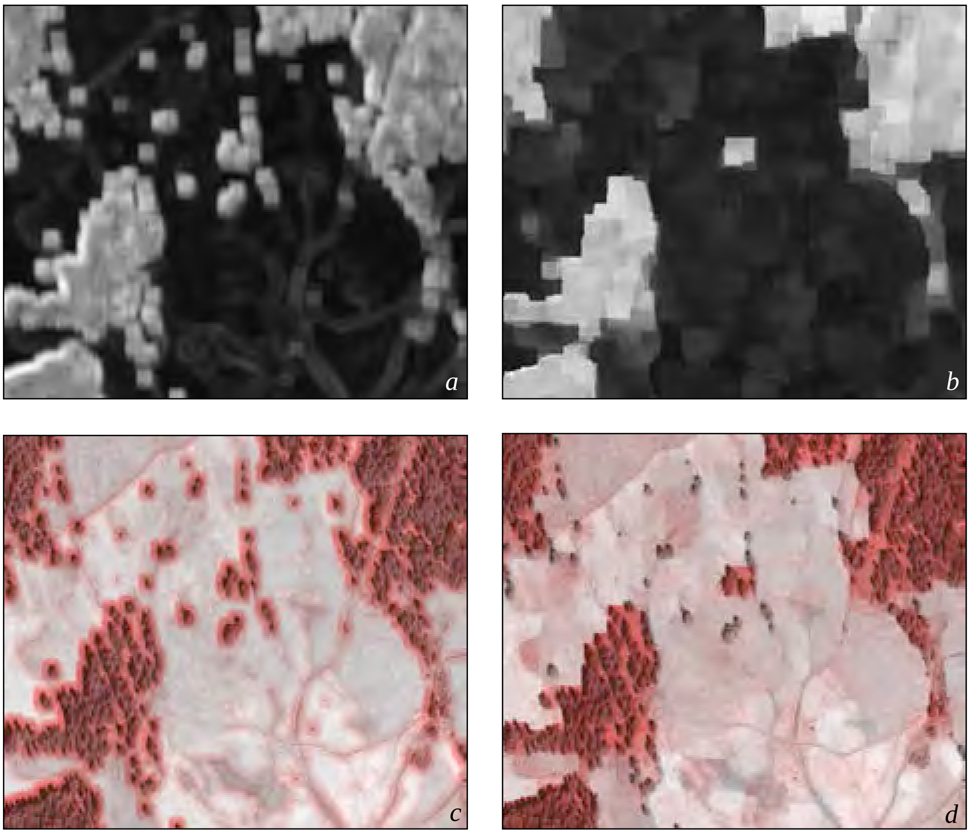

Figure 4. *Qualitative comparison of transformations that can be used for localization of textured areas. A square analysis window of equal size (40x40 pixels) was used in both transformations. The input image is shown in Fig. 3. (a) Variance based texture contrast descriptor. (b) The MTC descriptor. (c) Variance based texture contrast descriptor superimposed on the initial grey tone image. The contrast of red tones is proportional to the value of the descriptor. (d) The MTC descriptor superimposed on the initial grey tone image. The contrast of red tones is proportional to the value of the descriptor.*

filters out high contrast textured regions irrespectively of texture type. Since the objects of our interest are located in open grassland, i.e., outside the above-mentioned areas, this procedure reduces the number of false detections without affecting sensitivity to true examples. Filtering out textured areas also greatly reduces computational burden since the developed texture detection algorithm employs a sequence of morphological operators that are much faster than algorithms for the detection of geometrical structures of interest.

7. Morphological Texture Contrast (MTC) Transformation

The approach we introduced recently (Zingman et al. 2012) aims at detecting high contrast texture regions of different types. It is based on mathematical morphology, which has proven to be very efficient in the processing of remotely sensed images (Soille and Pesaresi 2002). We call our approach Morphological Texture Contrast (MTC) transformation.

In comparison to many other texture detection approaches developed to discriminate different types of texture, the MTC transformation is insensitive to texture properties except of texture contrast. It is intended to discriminate smooth regions corresponding to our regions of interest from regions with high contrast texture, such as forests, urban or rocky areas in remotely sensed images. An essential property of our detector is the ability to provide a low response at isolated or individual features, even if they are of a high contrast, a result that is currently not achieved by other techniques.

A commonly used technique to detect texture is to measure the local standard deviation of grey level within an analysis window moving over the whole image (Gonzalez and Woods 2001). We refer to this technique as a variance-based technique. It produces a response proportional to the texture contrast, thus allowing texture regions to be detected. However, it also produces a high response at isolated features (Fig. 4a), which in our case

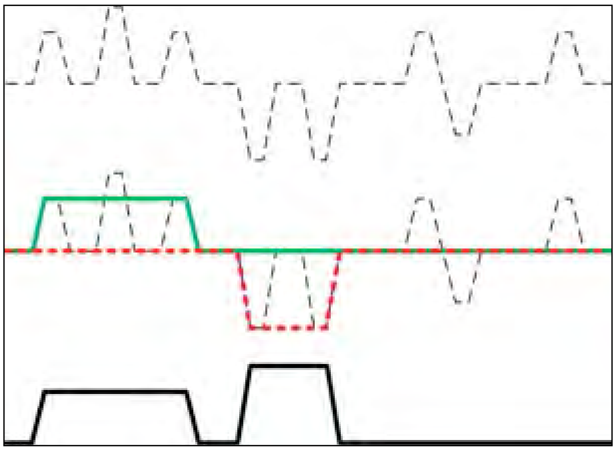

***Figure 5**. Top: A 1D signal composed of two textured regions and two isolated features on the right side. Middle: the green signal is an upper texture envelope; the red dashed-line signal is a lower texture envelope. Bottom: The MTC transformation. It is proportional to texture contrast and yields suppressed response at isolated features. Note that the salient feature on the top of the left texture (in the middle) is also suppressed.*

is unacceptable. Another disadvantage of the variance-based measure is that it blurs the borders of texture regions, which may result in inaccurate texture localization (Fig. 4c). Modifications of the variance-based technique are frequently used to generate a contrast feature within a set of other descriptors to discriminate textures (see, for example, Ojala et al. 2002).

The MTC transformation was developed as an alternative approach based on morphological alternating filters, namely morphological closing followed by opening and opening followed by closing (Serra 1988, Soille 2003). These operators are usually used for the suppression of noise in images. We use these operators to build a transformation proportional to texture contrast. The MTC transformation is obtained by taking non-negative values of the difference between morphological closing followed by opening and opening followed by closing. Negative values of the difference are substituted by zero values at the output of the MTC. This transformation results in high response at textured areas and low response at isolated features and in smooth regions.

While in our project the MTC transformation is applied to 2D images, the underlying idea is more easily explained by using an artificial 1D signal as shown in figure 5. The MTC transformation measures the difference between the upper and lower envelopes of texture providing a response proportional to texture strength. These envelopes, obtained using alternating morphological filters, coincide at isolated features, resulting in a suppressed response at such features. This capability of the MTC transformation is not available in other approaches.

Figures 6c and d illustrate the MTC transformation applied to 2D aerial and satellite images of 0.5m resolution shown in figures 6a and b. High response, corresponding to bright grey values, is generated in texture areas, while low response is produced in smooth areas and at isolated features. Low response at isolated features, such as individual trees, can be more clearly seen in the zoomed area shown in figure 4b that was cropped from the left corner of figure 6c. Figure 4d emphasizes how accurately texture regions are aligned with the regions of high values of the MTC descriptor.

The distribution of grey levels in the transformed images is highly bi-modal, with one mode corresponding to texture regions (high grey tone values) and the other to smooth regions (low grey tone values). These two modes can easily be separated by finding an appropriate threshold. This provides us with a segmentation that defines two disjoint masks for texture and smooth areas. We used the Otsu thresholding method (Otsu 1979) to find an appropriate threshold automatically. This approach corresponds to an unsupervised classification scheme since input data does not need to be labeled. The segmentation results in figs. 6e and f are superimposed on the initial images to emphasize the alignment of the results with the original data. As can be seen, the segmentation is quite accurate at the borders of texture regions.

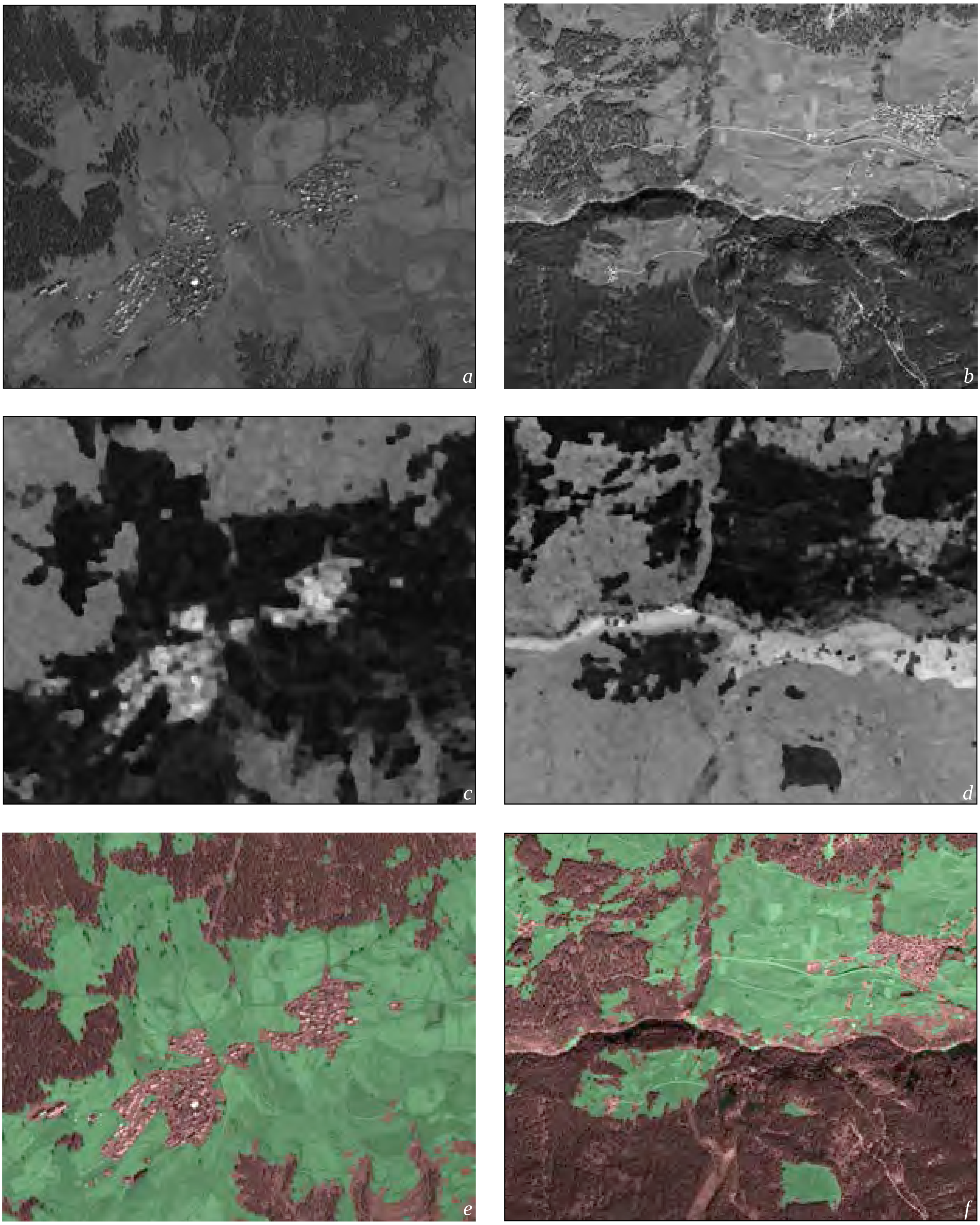

***Figure 6**. (a) Pan-chromatic image of 4000x3500 pixel size and 0.5m pixel resolution captured by the GeoEye-1 satellite (© GeoEye 2011, distributed by e-GEOS). (b) Aerial SWISSTOPO image of 6100x5000 pixel size and 0.5m pixel resolution. Scenery in both images includes high contrast textured regions (urban and forest areas) and comparably smooth field areas. (c) and (d) The MTC descriptor applied to both input images. (e) and (f) The segmentation result superimposed on the original images as obtained by automatic thresholding of the MTC descriptor. Brownish areas correspond to high contrast textured regions.*

In cases of highly varying sizes of texture and smooth areas in a given image, one of the two modes of the histogram (of the image transformed by the MTC operator) may be too small to reliably find an appropriate threshold. In such cases, the user can chose to use a supervised approach in which they are asked to manually delineate several representative regions of texture and smooth areas. Then a simple supervised classification technique in one dimension may be employed, e.g., the nearest distance (nearest mean) classification (Duda et al. 2001). Since manual delineation does not need to be accurate, it can be performed easily and quickly by a human operator.

So far, our tests showed the MTC transformation to be relatively fast. An image of 6100x5000 pixels is processed in about 21 seconds by our code written in Matlab installed on a standard PC equipped with an Intel Core2 Quad 2.83 GHz processor. This processing time corresponds to a square analysis window of 40x40 pixels. Our technique does not require parameter tuning except for a single scale parameter that defines the size of the analysis window. This parameter should just be roughly adjusted to the characteristic size of texture. For remotely sensed images it is related to their spatial resolution and the distances between objects on the ground. The technique is robust to illumination changes within the image and also works well with images from different sources. Though our technique was developed to analyse remotely sensed images, its application is not limited to this type of data.

8. Summary and Outlook

We have identified about 20 sites in the Silvretta region with ruins associated with alpine pastoralism. These sites serve as representative examples for the development of automated methods to detect similar sites in high-resolution satellite images. Using a texture segmentation technique that we recently developed, we segment the images into regions of interest and other regions based on texture contrast. This step is a prerequisite for object detection for which further steps have yet to be developed. By filtering out textured regions where no archaeological objects are to be expected, our approach will greatly reduce false detections.

In general terms, our approach follows successful examples of object detection in other fields by targeting a well-documented category of objects. While our sample is small, it can be used to develop methods that will later be tested and refined in other contexts. Our approach at image segmentation translates archaeological categories — regions where the archaeological objects we are interested in occur, and other regions where this is not the case — into categories of image properties, such as smooth image segments, and image segments with high texture contrast, respectively. While this approach may not always be as straightforward, in our view it is the direction to take in archaeological image analysis.

We are currently working on the method of actual object detection, the general outline of which is explained in section 5. While the outcome cannot fully be predicted at this time, we think it is important to proceed in this direction. Fieldwork in the Silvretta Alps will continue in the coming years. We will thus have sufficient opportunities to check the results of image analysis in the field. Once a functioning tool is available, it will be possible to test it in other regions with similar conditions through our network of cooperation partners working in alpine archaeology.

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