Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru

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Abstract
Illegal excavations represent one of the main risks which affect the archaeological heritage all over the world. They cause a massive loss of artefacts but also, and above all, a loss of the cultural context, which makes the subsequent interpretation of archaeological remains very difficult. Remote sensing offers a suitable chance to quantify and analyse this phenomenon, especially in those countries, from Southern America to Middle East, where the surveillance on site is not much effective and time consuming or non-practicable due to military or political restrictions.

In this paper we focus on the use of GeoEye and Google Earth imagery to quantitatively assess looting in Ventarrón (Lambayeque, Peru) that is one of most important archaeological sites in Southern America. Multitemporal satellite images acquired for the study area have been processed by using both autocorrelation statistics and unsupervised classification to highlight and extract looting patterns. The mapping of areas affected by looting offered the opportunity to investigate such areas not previously systematically documented. To this purpose Ground Penetrating Radar prospections were conducted in some looted sites.

1. Introduction

Archaeological resources may be adversely affected by a variety of man-made and natural risks. In many countries, such as Southern and Central America, Asia and Middle East, it is largely recognized that looting (unauthorized excavation) phenomena impact archaeological heritage and cultural landscape much more than other risk factors (Atwood, 2006; Brodie et al., 2001).

The pillaging of antiquities not only denies cultural heritage to the new generations but, above all, it causes the destruction of the cultural context in which the looted objects were found. This makes the interpretation of archaeological remains complex or impossible, thus causing an irreparable damage to cultural identity and to scientific research on the human past.

The plundering of archaeological sites is a global problem which is difficult to quantify because it is linked to the clandestine market system of antiquities. The worldwide extension of this phenomenon made necessary a strong international cooperation to define mitigation strategies. The problem started to be faced globally since 1956, when the General Conference of the United Nations Educational, Scientific and Cultural Organization recommended all the Member States to take “all necessary measures to prevent clandestine excavations and damage to monuments and also to prevent the export of objects thus obtained” (UNESCO, 1956). Following, in many countries repressive measures were adopted along with restrictive laws to impose the returning of objects derived from clandestine excavations or theft to their own countries.

In 1970, UNESCO promulgated the Convention on the Means of Prohibiting and Preventing the Illicit Import, Export and Transfer of Ownership of Cultural Property (UNESCO, 1970). This was another important advancement made by the international community to contrast site looting and illegal trade of archaeological objects.

At present there are several international conventions which together provide a framework to support the international cooperation to prevent looting, including for the underwater archaeology (UNESCO, 2001). Nevertheless, in spite of a new ethical attitude followed to the UNESCO conventions (Brodie and Renfrew, 2005), much more efforts must be still addressed to contrast looting and smuggling of artefacts.

To this aim, an effective approach is the surveillance based on the cooperation of public departments for the management and protection of cultural heritage, superintendencies, heritage
protection services and non-profit archaeological groups, which compose a synergic network (Brodie et al., 2001). Nevertheless it is time consuming, expensive and not suitable for vast areas (with surface greater than 10 sqkm) and for remote archaeological sites, characterized by difficult accessibility.

To cope with these critical conditions, in many countries (especially in Europe) the monitoring of the impacts of anthropic activities, including looting, is carried out by aerial surveillance. Its effectiveness depends on the capability to perform systematic surveillance, exploiting different vectors such as helicopter, airplane etc. Nevertheless, it is non practicable in several countries due to military, political restrictions, or due to ongoing conflicts and wars. Moreover, aerial surveillance is not much effective for huge areas and for difficult environmental settings (desert, rain forest, etc.).

In these contexts, satellite imagery with spatial resolution less than 1 mt, commonly named very high resolution (VHR) data, offer a suitable chance thanks to their global coverage and re-visititation times.

Some recent applications have shown that VHR satellite imagery are of great help in surveying and protecting cultural sites against the plundering of archaeological sites. This technology has been used in Iraq to survey and quantify the looting damage on the archaeological heritage during the last armed conflicts (Stone, 2008; Van Ess et al., 2006). In particular, Stone (2008) estimated the extension of the damaged areas and the chronology of looting, by using a QuickBird time series. Van Ess et al. (2006) were able to identify looted areas near Uruk-Warka, situated c. 300 km south of Baghdad, by comparing pre-war and post war IKONOS images. They located looting activities by using supervised classification methods. In Egypt, the comparison between historical maps and high resolution satellite time series put in evidence that the 88% of the overall sites were lost over the past two centuries years and the majority of destructions occurred in the last 40 years (Parcak, 2007).

In Peru, Contreras (2010) used remote sensing imagery from aerial and space platforms to assess looting damage via photointerpretation in the Virú valley.

From the data analysis point of view, a contribution has been provided by Lasaponara and Masini (2010) who devised a semi-automatic data processing approach applied to some areas of Southern Peru. They used local indices of spatial autocorrelation (LISA) to enhance locating spatial patterns typically characterized by circular holes.

The highly satisfactory results, validated by ground survey (Lasaponara et al., 2012), encouraged the authors of this paper to further improve the semi automatic approach. In particular, the LISA has been integrated with convolution filtering and automatic classification to easily identify and map archaeological looting. Moreover, Ground Penetrating Radar (GPR) survey was used to observe the plundered areas beneath the surface. This approach has been applied to some areas of Northern Peru (see section 2), that have been extensively affected by looting over the years.

2. Study area

In Peru illegal excavations date back to the Spanish colonial period (Silverman, 1993). They strongly increased in the fifties and in the sixties of the 20th century, as occurred in several sites in the southern cost (see Fig. 1).

Today, looting is still a pressing problem (Alva, 2001).

When a new site comes to public notice, “it is often because ‘treasure hunters’ and professional looters have already been there” (BBC, 15 December 2011, http://www.bbc.co.uk/news/world-latin-america-16190824).

Illegal diggings are pervasively and extensively present due to a mixture of social problems and complex situations that are strongly connected with an upsurge in the illicit trade of antiquities.

From the anthropological point of view, looters have highly variable characteristics, such as: (i) small-scale looters who are generally hikers, hunters considered as unpremeditated looters, (ii) artefact collectors who damage sites to build their own collections of ancient artefacts, and (iii) “professional” looters who may be poor native people or relatively educated, non-indigenous individuals motivated by money, coming from a well-established international market (Smith, 2005). Until the early of the 20th century the grave robbers, named huajeros in Peru, used to work mainly individually, in the subsequent decade they started to work in teams for their own gain or for second parties.

Lambayeque region, in North Peru, represents an emblematic case for the looting and rescue archaeology in Peru (Fig. 2). The well known discovery of the Royal Tombs of Sipan in 1989 was made.

Fig. 1. 1955 Aerial image of the Ceremonial Centre of Cahuachi. The photo shows a wide area affected by circular holes made by grave robbers.

Fig. 2. Typical looting patterns in Lambayeque from aerial view (courtesy by Ignacio Alva).
after a “disagreement amongst looters” involved in an illegal excavation. This quarrel caused the intervention of the police and the involvement of local archaeologists, Walter Alva and Susana Menezes, to examine the looted objects (see Watson, 1999). As a consequence, archaeological rescue started and the following systematic researchers and excavations enabled the discovery of one of the richest tomb area in South America. The recovered objects were stored and exhibited in the Royal Tombs of Sipán Museum which is one of the biggest museums in Peru.

The study area focused in the current investigation is located in Ventarron, at about 20 Kms from Sipán. Ventarron is characterized by an extraordinary cultural continuity, covering more than 4000 years. A 4000-year old temple covering about 2500 square m, started to be excavated in 2007 by Walter Alva, who unearthed probably the oldest wall painting ever discovered in America (Hearn, 2007).

In the last five years the archaeological research has been enlarged to the territory surrounding Ventarron, including Arenal, which is placed on a sandish area at the foot of the western slope of Cerro Ventarron. A rich archaeological record dated back from the Initial period (1800–900 BC) to Moche age (100 AD–800 AD) was found. Unfortunately, the area has been devastated by continuous plundering and profanation of tombs which reduced the potential archaeological resources, thus making the understanding and reconstruction of the different phases of human frequentation very difficult.

Within our activities in the framework of the ITACA mission (Masini et al., 2012), mainly focused on archaeogeophysical investigations, we have been asked by the local archaeologists to help them in detecting, mapping and assessing the damage caused by looters. To this aim, we used satellite imagery and geophysical techniques. We mainly focused on areas close to Arenal and Cafetal (Fig. 3). The latter is situated in the southern slope of Cerro Ventarron and is characterized by archaeological remains ranging from Lambayeque phase to the Chimú Inka age (900–1400 AD). Cafetal, likewise Arenal, has been strongly damaged by an intensive looting activity in the last three decades.

2.1. Methodological approach and dataset

Our approach was based on the use of both satellite data and georadar method:

1) to experience with an image processing procedure which allows us to make the identification of looting patterns easier;
2) to perform a multitemporal analysis of looting activity by exploiting the available multitemporal dataset;
3) to map the looted areas;
4) to evaluate the georadar method and explore in-depth some looted area.

2.2. Satellite dataset

The images used for this study have been a scene provided by Google Earth acquired on 30/12/2003, GeoEye multispectral imagery acquired on 09/09/2010 (at 15:41), and ASTER images acquired on 01/03/2001.

GeoEye is the highest resolution imaging instrumental satellite platform. It collects images with a ground resolution of 0.41-m in the panchromatic and 1.65 m in the multispectral bands, resampled to 0.5 and 2 m, respectively.

ASTER sensor flies on the Earth Observing System (EOS) Terra satellite and collects data in the visible/near infrared (VNIR), short wave infrared (SWIR), and thermal infrared bands (TIR), for a total of 15 spectral bands. One telescope of the VNIR system is nadir looking and two are backward looking, allowing for the construction of 3-dimensional digital elevation models (DEM) due to the stereo capability of the different look angles. The DEM has been used to wrap the satellite imagery of the two study areas. A more detailed DTM for Arenal has been obtained by a topographical survey at 1/2000 scale.

2.3. Satellite data processing: rational basis

The data processing chain employed for this study can be summarised in two steps: 1) extraction of spatial patterns linked to illegal excavation using geostatistical analysis and 2) the automatic classification of looting and mapping, applied to both the Google Earth picture (30/12/2003) and GeoEye multispectral imagery (09/09/2010). For the GeoEye multispectral imagery before applying the steps 1 and 2, pansharpening was performed to exploit the higher spatial resolution of the panchromatic image and the multispectral properties of the spectral channels.

2.3.1. Pansharpening

Pan-sharpening provides a spatial enhancement of the lower resolution multi-spectral (MS) data. Equivalently, we can observe that pan-sharpening increases the spectral resolution of the panchromatic (Pan) image having a higher spatial resolution, but a lower spectral resolution bearing no spectral information.
Pansharpening can be summarised in two steps: 1) extraction of high-resolution geometrical information from the panchromatic image; 2) injection of such spatial details to the interpolated low-resolution MS bands through proper models.

Among the available algorithms (Lasaponara and Masini, 2012), for this study Gram Schmidt (GS) method (Laben et al., 2000), available in ENVI software, on the basis of our previous experience in similar environmental conditions, in Southern Peru (Lasaponara et al., 2011).

2.3.2. Geostatistical analysis

Satellite data from VHR sensors can provide invaluable information at a spatial resolution quite close to the spatial detail offered by aerial photo. Nevertheless, the identification and extraction of features of interest may pose serious challenges related to data processing and interpretation. This is mainly due to the fact that the targets/features are generally not isolated, but mixed with others and they may appear even quite different within the same image due to their diverse physical characteristics. This complexity is more evident for features characterized by weak spatial/spectral signals and, therefore, do not exhibit clear and clean edges and/or patterns. Moreover, there are numerous factors, such as, atmospheric contamination, seasonal variability, noise, etc. that tend to distort subtle edges and feature patterns. So, the use of robust data processing techniques is required to identify, extract and collect as much information as possible. In this context, the use of statistical spatial analyses may be quite effective because they take into account not only the spectral values of the given pixel but also pixel spatial relationships. This enables us to identify homogeneity and heterogeneity, similarity and dissimilarity, patches and gradients as well as to capture data variability and to recognize patterns, as in the case of the current investigations focused on circular holes linked to archaeological looting.

Over the years, various methods have been developed for modelling geospatial proximity, dependency and heterogeneity in order to refer and inform us about relations among geospatial objects/targets/features. Among the numerous computational approaches and modelling we briefly focus on the following: (i) spatial dependency or spatial autocorrelation which refers on observations that are close to each other and have similar values; (ii) spatial proximity (or location-based similarity) which informs us about value similarity (Anselin, 1995); (iii) spatial heterogeneity which refers to the non-stationary nature of the geographic processes.

Dependency (or spatial autocorrelation) and heterogeneity are the two properties of spatial phenomena which have been widely used to gain new insights into geographic phenomena. Over the years, both global and local parameters have been set up in order to reflect well the process occurring at a given location.

Several tools, such as local indicators of spatial association by Anselin (1995) or the geographically weighted regression by Fotheringham et al. (2002), have been developed as knowledge-based approaches to better enhance and detect clusters and patterns improving results from traditional pixel-based analysis.

In this paper, we use the concept of spatial autocorrelations which takes into account the spatial attributes of geographical objects under investigation, evaluates and describes their relationship and spatial patterns. Spatial patterns are defined by the spatial arrangement of individual entities and by their spatial relationships. Spatial autocorrelations in the field of archaeological investigations measure the extent to which the occurrence of one object/feature/site is influenced by similar objects/features/sites in the adjacent areas. As such, statistics of spatial autocorrelation provides: (i) indicators of spatial patterns and (ii) key information for understanding the spatial processes underlying the distribution of features under observation.

Geographical observations should be arranged in spatial and temporal order, by latitude and longitude, and historical periods. In this context satellite time series data can provide useful information on looting activities over the years.

As for any type of dataset, also in the case of digital image analysis there are many indicators of spatial autocorrelation that can be distinguished into the following: Global indicators, Local indicators.

2.3.3. Global indicators of spatial autocorrelation

Global statistics summarize the magnitude of spatial autocorrelation for the entire region by a single value. The Global indicators of autocorrelation utilize distance to define the neighbourhood of a region and measure if and how much the dataset is autocorrelated in the entire study region.

One of the principal global indicators of autocorrelation is the Moran’s index $I$ (Moran, 1948), defined by formula

$$
I = \frac{N \sum_{i} \sum_{j} wij (X_i - \bar{X}) (X_j - \bar{X})}{\sum_{i} \sum_{j} wij (X_i - X_j)^2}
$$

where $N$ is the total pixel number, $Xi$ and $Xj$ are intensity in points $i$ and $j$ (with $i \neq j$), is the average value, $wij$ is an element of the weight matrix.

$le [-1; 1]$; if $le [-1; 0]$ there is negative autocorrelation; if $le (0; 1]$ there is positive autocorrelation.

Theoretically, if $I$ converges to 0 there is null autocorrelation. In this case the expected value of Moran’s $I$ is

$$
E(I) = \frac{-1}{N - 1}
$$

where $N$ is the number of events in the whole distribution.

The second global indicator of spatial autocorrelation is the Geary’s $C$ (Geary, 1954), expressed by Formula 3:

$$
C = \frac{(N - 1) \sum_{i} \sum_{j} wij (X_i - X_j)^2}{2wij (X_i - \bar{X})^2}
$$

where symbols have the same meaning than expression 1.

$Ce [0; 2]$; if $Ce [0; 1]$ there’s positive autocorrelation; if $Ce (0; 2]$ there’s negative autocorrelation; if $C$ converges to 1 there’s null autocorrelation.

2.3.4. Local indicators of spatial autocorrelation

The local version of statistic utilizes distance information to identify local clusters and relies on the distance information captured in Distance matrix. Values indicating the magnitude of spatial association can be derived for each areal unit, namely for each pixel in the case of digital image.

The most common Local Indicators of Spatial Autocorrelation are: Local Moran’s $I$ (Anselin, 1995), Local Geary’s $C$ (Cliff and Ord, 1981), and Getis-Ord Local $Gi$ (Getis and Ord, 1994; Illian et al., 2008).

Local Moran’s $I$ index is defined according to Formula 4.

$$
I_i = \frac{(X_i - \bar{X})}{\bar{X}} \sum_{j=1}^{N} (wij (X_j - \bar{X}))
$$

Local Geary’s $C$ Index is defined according to Formula 5.
algorithm assigns means clustering (MacQueen, 1967), (ii) ISODATA (Iterative Self-
applications is that: (i) it is an automatic process, namely, it nor-
the number of clusters is known
be carried out. The only difference is that the K-means assumes that
are quite similar. In both of them the user has only to indicate (i) the
is really important before running the classi
riety of subtle features.
provide improved performance also for scenes that contain a va-
ction of results from spatial
2.3.5. Automatic classiﬁcation of results from spatial autocorrelation applied to satellite image
Subtle features linked to small variations are really complex and
mental applications is that: (i) it is an automatic process, namely, it nor-
certain threshold or if the centres of two clusters are within a
threshold. ISODATA algorithm is considered more ﬂexible compared to the K-means method, but it requires the empirical selec-
For this reason, in this study we applied K-means method, with the following selected parameters: number of classes = 5, change threshold = 5%.
2.4. GPR background theory
Ground Penetrating Radar (GPR) is an EM geophysical method for high-resolution detection, imaging and mapping of subsurface soils. In principle, and just to introduce the subject, the GPR can be viewed as composed by a central unity, a transmitting and a receiving antenna, and a computer. The central unity generates electromagnetic (EM) pulses that are radiated into the soil by the transmitting antenna. Rigorously, the pulses are radiated in all the directions, but most energy is radiated within a conic volume under the antenna. When the EM waves meet any buried discontinuity (a buried object, or also the interface between two geological layers, a cavity, a zone with different humidity etc.), they are scattered in all the directions (the intensity of the scattered power is not spatially uniform, but depends on the scattering target) and so partly also toward the receiving antenna. Usually the transmitting and the receiving antenna are incorporated in a rigid structure and move together. In modern systems, the gathered signal is represented in real time on the screen of the computer, and is stored in the hard disk memory of the computer. Most of the returned signals in radar profile are reflections from subsurface discontinuities, although other types of waves may also be present. Wave types such as a direct airwave, a critically refracted airwave and a direct ground wave generally appear as well, as predicted by the Ray. Note that most of the signals in the proﬁles are reﬂections except the two topmost, which are two direct waves from the transmitter to the receiver, one in the air and the other in the ground.
In certain common conditions during GPR investigations, in addition to reﬂections, the EM waves undergo diffractions from small inhomogeneities and objects. Diffractions that can be identiﬁed as hyperbolae in the time section occur in two cases: when the dominant wavelength, λ, in the radar pulse is larger than the dimensions of the diffractions source (Conyers and Goodman, 1997), and when waves are diffracted from sharp edges. The physical relation between the velocity, v, wavelength, λ, and fre-
frequency, f, of an EM wave is given by the equation (Conyers and Goodman, 1997):

\[ C = \frac{n - 1}{\sum_{i=1}^{n} (X_i - \bar{X})^2} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{w_{ij}(X_i - X_j)^2}{2 \sum_{j=1}^{n} \sum_{i=1}^{n} w_{ij}} \]  

(5)

Getis and Ord’s Gi is deﬁned according to Formula 6.

\[ G_i(d) = \frac{\sum_{i=1}^{n} w_i(d) X_i - \bar{X}}{\sqrt{(N-1)\sum_{i=1}^{n} w_i(d) - \left(\sum_{i=1}^{n} w_i(d)\right)^2}} \sqrt{\frac{N-2}{N-C_0}} \]  

(6)

These indicators show a different concept of spatial association:
1) Local Moran’s I: a high value of the index means positive corre-
lation both for high values and for low values of intensity;
2) Local Geary’s C detects areas of dissimilarity between events;
3) Getis and Ord’s Gi: a high value of the index means positive corre-
lation for high values of intensity, while a low value of the
index means positive correlation for low values of intensity.

Such geostatistical analysis tools are available in several com-
mercial softwares, ranging from Geographic Information System
(GIS) and image processing ones. For the current study we used the
routines of the ENVI software.

The neighbourhood rule used is the so-called Quen’s Case which
selects all eight neighbouring pixels.

2.3.5. Automatic classiﬁcation of results from spatial autocorrelation applied to satellite image
Subtle features linked to small variations are really complex and
traditional techniques, as a pixel-based classiﬁcation, may be not
effecti. Subtle changes linked, for example to illegal excavations
may be characterized by different features which cannot be char-
acterized by any speciﬁc colour or tone of grey in the image, but
rather they can be characterized by their heterogeneity. To cope
with this drawback, spatial autocorrelation is applied to satellite
image as pre-classiﬁcation step to make the classiﬁcation easier. It
is really important before running the classiﬁer to make the change
feature pattern easily recognizable.

The use of this integrated approach, that combines the
enhancement of features with unsupervised classiﬁcation may provide improved performance also for scenes that contain a va-
riety of subtle features.

Unsupervised classiﬁcation only requires a limited human
intervention to have the foreknowledge of the classes. The impor-
tance of applying unsupervised classiﬁcation in archaeological
applications is that: (i) it is an automatic process, namely, it nor-
maically requires only a minimal amount of initial input, compared to
supervised data set; (ii) classes do not have to be deﬁned a priori;
(iii) unknown classes may be discovered.

A number of unsupervised classiﬁcation algorithms are commonly used in remote sensing, among them we outline (i) K-
means clustering (MacQueen, 1967), (ii) ISODATA (Iterative Self-
Organizing Data Analysis Technique; Ball and Hall, 1965) which
are quite similar. In both of them the user has only to indicate (i) the
number of the predeﬁned classes (clusters) and (ii) the iterations to
be carried out. The only difference is that the K-means assumes that
the number of clusters is known a priori whereas the ISODATA al-
gorithm assigns “dynamically” the different number of clusters.
Both these algorithms are iterative procedures, based on the
following steps: (i) they ﬁrst assign an arbitrary initial cluster
vector, (ii) each pixel is classiﬁed to the closest cluster, (iii) new
cluster mean vectors are calculated based on all the pixels in one
cluster. The second and third steps are iteratively repeated until the
“variations” between the iteration is small. Such variations can be
computed and assessed in several different ways. For example, in
the K-means algorithm, the cluster variability is optimized by
minimizing the sums of square distances (errors) expressed by
equation (1).

\[ \text{MSE} = \frac{\sum [x - C(x)]^2}{N - c} \]  

(7)

where N is the number of pixels, c indicates the number of clusters,
and b is the number of spectral bands, C(x) is the mean of the
cluster that pixel x is assigned to.

Equation (7) clearly shows that the minimization of MSE implies
that K-means works best for spherical clusters that have the same
variance. This indicates that K-means algorithm tends to perform
better for homogeneous surface/object as desert area.

The ISODATA algorithm merges or splits clusters if, respectively,
the number of pixels belonging to a given cluster is less than a
certain threshold or if the centres of two clusters are within a
threshold. ISODATA algorithm is considered more ﬂexible compared to the K-means method, but it requires the empirical selec-
tion of many more parameters.

For this reason, in this study we applied K-means method, with the following selected parameters: number of classes = 5, change threshold = 5%.
According to Eq. (8), if, for example (Leucci, 2012), a GPR signal were transmitted at a centre frequency of 100 MHz into geological environment with an average propagation velocity of 0.1 m/ns, the local dominant wavelength of the propagating signal would be approximately 1 m.

Therefore, diffraction patterns would be obtained from objects or inhomogeneities that are smaller than 1 m.

The resolution of a GPR image is controlled by the sharpness of the focus of the system. The resolution is defined by the Rayleigh criterion (Reynolds, 1998) as the ability to distinguish between two close signals obtained during the GPR mapping, before their separate identity is lost and they appear to be one event. The range resolution, can be practically defined as the half-wavelength of the GPR signal in the geological medium (Conyers and Goodman, 1997). Processing methods such as deconvolution can enhance the range resolution below a quarter of the wavelength (Widess, 1973). For example (Leucci, 2012), the calculated average basic vertical resolution for a 100 MHz centre frequency mapping of a 0.1 m/ns environment is about 0.5 m (0.125 m). A reflecting horizon may vary laterally in dielectric constant, thus changing the reflection coefficient, or stop laterally, as a result of faulting or absence of deposition (e.g., channel sands). Horizontal (or spatial) resolution refers to the ability to detect the lateral changes in reflectors, such as those caused by faults or facies changes. In this case, the reflected energy that arrives at the receiver antenna does not come from a single point of incidence, but from a circular zone on the reflector. If “t” is the two-way time of a reflection, “fc” the frequency of a radar wave and “v” the velocity, the first Fresnel zone radius “Fr” from which most energy comes, is (Reynolds, 1998):

\[ Fr = \frac{0.5v(t/2fc)}{2} \]  

(9)

The derivation of the Fresnel zone radius approximation for GPR is exactly analogous for seismic waves, although in reality, since GPR systems generally use directional dipole antennas, the EM sheaf of waves forms the shape of an elliptical cone (the long axis is perpendicular to the dipole). According to Equation (9), if the area of a reflector is greater than an area bordered by circular zone with radius Fr, its shape will be accurately mapped on the time section. However, if the areal extent of the reflector is smaller, diffraction patterns from the edges may dominate its shape. From Equation (9), (fl) the first Fresnel zone radius “fr” from which most energy comes is (Leucci, 2012):

\[ fl = \frac{0.5v(t/2fc)}{2} \]  

(8)

2.6. GPR data processing

One of the great advantages of the GPR method is the fact that the raw data is acquired in a manner that allows it to be easily viewed in real time using a computer screen. Often very little processing is required for an initial interpretation of the data, with most of the effort directed towards data visualization. On the other hand, depending on the application and target of interest, it may be necessary to perform sophisticated data processing, and many practitioners find that techniques common to seismic reflection such as migration can be applied. The outcome of processing is a cross-section of the subsurface EM properties, displayed in terms of the two-way travel time, i.e. the time taken for a wave to move from the transmitter to a reflector and return to the receiver. The amount of processing undertaken can range from basic, which allows raw data output, to the more time consuming application of algorithms designed for use on seismic dataset (Yilmaz, 1987), which produces high quality output (Daniels et al., 1988; Conyers and Goodman, 1997). The processing sequence usually developed for GPR raw data is following done.

zero-time adjust (static shift) – During a GPR survey, the first waveform to arrive at the receiver is the air wave. There is a delay in the time of arrival of the first break of the air wave on the radar section due to the length of the cable connecting the antennas and the control unit. Therefore need to associate zero-time with zero-depth, so any time offset due to instrument recording must be removed before interpretation of the radar image.

Background removal filter (subtract average trace to remove banding) - Background noise is a repetitive signal created by slight ringing in the antennas, which produces a coherent banding effect, parallel to the surface wave, across the section (Conyers and Goodman, 1997). The filter is a simple arithmetic process that sums all the amplitudes of reflections that were recorded at the same time along a profile and divides by the number of traces summed the resulting composite digital wave, which is an average of all background noise, is then subtracted from the data set. Care must be taken in this process not to remove real linear events in the
profile. The time window where the filter operates must be specified so that the filter is not applied until after the surface wave.

**Gain** — Gain is used to compensate for amplitude variations in the GPR image; early signal arrival times have greater amplitude than later times because these early signals have not travelled as far. The loss of signal amplitude is related to geometric spreading as well as intrinsic attenuation. Various time-variable gain functions may be applied in an effort to equalize amplitudes of the recorded signals. The most commonly applied is an automatic gain control (AGC) that is a time varying gain that runs a window of chosen length along each trace, point by point, finding the average amplitude over the length of the window about each point. A gain function is then applied such that the average at each point is made constant along the trace.

**Topographic corrections** — Surveyed elevation data are used to apply topography to the GPR survey profiles. Firstly trace windowing is applied to the data to remove all artefacts in the survey that arrived before the time zero arrivals. The actual elevation recorded along the GPR line are then entered into the data processing package and the time zero arrivals are hung from the topographic profile by applying a time shift to each individual trace.

**Frequency filtering** — Although GPR data are collected with source and receiver antennae of specified dominant frequency, the recorded signals include a band of frequencies around the dominant frequency component. Frequency filtering is a way of removing unwanted high and/or low frequencies in order to produce a more interpretable GPR image. Highpass filtering maintains the high frequencies in the signal but removes the low frequency components. Low-pass filtering does just the opposite, removing high frequencies and retaining the low frequency components. A combination of these two effects can be achieved with a band-pass filter, where the filter retains all frequencies in the pass band, but removes the high and low frequencies outside of the pass band.

**Migration** — Migration is a processing technique which attempts to correct for the fact that energy in the GPR profile image is not necessarily correctly associated with depths below the 2-D survey line.

Migration can be seen as an inverse processing step which attempts to correct the geometry of the subsurface in the GPR image with respect to the survey geometry. For example, a subsurface scattering point would show up in a GPR image as a hyperbolic-shaped feature. Migration would associate all the energy in the wavelets making up the hyperbolic feature with the point of diffraction, and imaging of the actual earth structure (the heterogeneity represented by the point diffractor) would be imaged more clearly. Migration operators require a good estimate of subsurface EM wave velocity in order to apply the correct adjustments to the GPR image. For more see Yilmaz (1987).

### 3. Results and discussion

#### 3.1. Satellite remote sensing

Two test sites have been selected in Cafetal and Arenal, named A and B, respectively (see Fig. 3). These test sites were selected because they had been affected by intense pillaging in the last decade, and moreover are characterized by different size of circular holes linked to looting. They are deeper and smaller in Cafetal, shallower and larger in Arenal. In particular with regard to the depths, we observed average values around 70–90 cm in Cafetal and 40–50 cm in Arenal; with regard to the diameters, we measured average values of 2.6 m in Cafetal and 3.9 m in Arenal (see Table 1).

Fig. 4 shows two satellite images both related to the Area A in Cafetal acquired on 2003 and 2010, respectively. On the left hand side of the image there is a Google Earth scene, on the right hand side an RGB of GeoEye-1 imagery is showed. The latter exhibits the typical spatial pattern due to looting activity with circular holes carried out between 2003 and 2010.

In order to make easier the identification and mapping of the circular holes of the looted area (see section 4.2.1 and 4.2.3), LISA have been applied to multispectral GeoEye-1 imagery.

In Fig. 5, the upper scene shows the red pan-sharpened band which is more significant for the detection of the circular holes with respect to the other spectral bands, including the panchromatic channel. In the middle of the same figure, from left to right, a zoom of the red pan-sharpened band, the results of Moran, Geary and Getis-Ord indices are shown, respectively. All these images are enhanced by High Gaussian high pass filtering. The lower part of Fig. 5 shows the results of Kmeans classifications of red pan-sharpened, Moran, Geary and Getis-Ord indices.

As expected the Moran's I is able to detect both positive and negative spatial correlations, but clustering of high or low values are not distinguished (Moran, 1948). In particular, it performs pixel clustering, discriminating bushes, grave robbers holes (H) and unlooted soil (UL). These different targets are characterized by diverse textures and spectral values. The Kmeans classification of Moran results enhances the different targets which are clearly identified. Therefore, they belong to diverse classes: the green class is related to H, the blue one denotes UL targets in between the holes. Finally, the cyan and yellow ones identify darker and lighter green vegetation, respectively.

The result of Geary-Ord index highlights edges and areas characterized by a high variability between a pixel value and its neighbours. Therefore, it is not able to discriminate vegetation from soil, including looted and non looted areas. This is also confirmed by the classes provided by the Kmeans algorithm. Nevertheless, in absence of vegetation, Geary index is able to better discriminate the holes respect to its surrounding, as also confirmed by Kmeans classification.

Getis-Ord identifies hot spots, namely areas characterized by very high or very low values compared to those of neighbouring pixels. The Getis-Ord result appears as a low pass filtering thus making easier the survey of the shadowed circular holes. The subsequent classification does not add meaningful information respect to the previous classifications of Moran and Geary products.

In Arenal (see Fig. 6), the selected test site (Area B) puts into evidence significant changes of the pattern linked to plundering. The multitemporal comparison shows two important facts: I) the enlargement of the looted areas, in the south-western part, thus evidencing an increasing of the looted area of about 36% (0.74 Ha in 2003, 1.01 Ha in 2010; see Fig. 6); II) the effects of the eolic erosion makes less evident some holes partially filled by desert sand over the years in the 2010 scene.

For the Arenal test site we used the same data processing as for Cafetal.

### Table 1

<table>
<thead>
<tr>
<th>Site</th>
<th>Name of area</th>
<th>Surface (Ha)</th>
<th>D 90% (mt)</th>
<th>D_average (mt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cafetal A</td>
<td>0.36</td>
<td>2.2–3.2</td>
<td>2.6</td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>0.21</td>
<td>2.3–3.4</td>
<td>2.9</td>
<td></td>
</tr>
<tr>
<td>A2</td>
<td>0.35</td>
<td>2.5–4.2</td>
<td>3.8</td>
<td></td>
</tr>
<tr>
<td>A3</td>
<td>0.185</td>
<td>3.7–4.5</td>
<td>4.2</td>
<td></td>
</tr>
<tr>
<td>A4</td>
<td>0.16</td>
<td>2.3–3.1</td>
<td>2.8</td>
<td></td>
</tr>
<tr>
<td>Arenal B</td>
<td>1.01</td>
<td>3.2–4.6</td>
<td>3.9</td>
<td></td>
</tr>
<tr>
<td>B1</td>
<td>0.28</td>
<td>4.2–5.1</td>
<td>4.8</td>
<td></td>
</tr>
<tr>
<td>B2</td>
<td>0.9</td>
<td>4–6.3</td>
<td>5.1</td>
<td></td>
</tr>
<tr>
<td>B3</td>
<td>0.35</td>
<td>3–4.2</td>
<td>3.8</td>
<td></td>
</tr>
</tbody>
</table>
In Fig. 7, the upper scene shows the red pan-sharpened band which as for Cafetal better enhances the circular holes compared to the other spectral channels. In the middle of the same figure, a zoom of the red band along with the results obtained from Moran, Geary and Getis-Ord indices are shown from left to right, respectively. Finally, the lower part of Fig. 7 shows the results of Kmeans classifications of the above listed images.

As a whole, in Arenal the LISA approach appears to be less effective than in Cafetal. This is undoubtedly due to the shallower depths of the holes due to the eolic erosion, which tends to fill the

Fig. 4. Area A in Cafetal from 2003 Google Earth scene (left hand panel) and from 2010 GeoEye imagery (right hand panel). The comparison of the two scenes puts into evidence illegal excavations carried out between 2003 and 2010.

Fig. 5. Area A in Cafetal. Upper: red pan-sharpened band; Medium, from left to right: zoomed detail of red pan-sharpened band, Moran, Geary and Getis indices applied to red band, respectively; lower, from left to right: Kmeans classification of the zoomed details. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
cavities over the time thus smoothing the relief. Nevertheless, as for Cafetal, Moran index and the following classification provided the best results in terms of spectral separability of the pits carried out by ‘huajeros’.

For both Arenal and Cafetal sites, the mapping of looted areas based on the 2010 GeoEye scenes has been carried out (see Figs. 8 and 9, respectively).

In Cafetal the total extension of the surfaces affected by plundering is 2.39 Ha. In Arenal the extension of looted areas is 3.15 Ha. The archaeometric analysis of the circular holes put into evidence different sizes for the two investigated sites: about 2.5 m in Cafetal and larger than 4 m in Arenal. This is due to different soil granulometry (mailingly sand in Arenal and sily sand in Cafetal) which determines different stability conditions of the cavities.

3.2. GPR data analysis and results

In this section we show a couple of examples of GPR prospecting on alleged looted tombs. In particular, we see “alleged” because (fortunately) the huajeros often perform useless trials, and the residual holes that we see does not correspond necessarily to an effective tomb and, even in this case, the looting was not necessarily completed. What we see is just a trial of looting. The two alleged looted tombs shown in this section were placed in Arenal, area B. In this site we have preformed several GPR campaigns. GPR data show meaningful returns from meaningful depths (we have estimated the depth of some returned echoes up to 5 m) but also from quite shallow targets in other points. The good penetration is due to the fact that the area is semi-desertic. From the hyperbolic tails of the GPR data, we have estimated a propagation velocity ranging from about 7 cm/ns to about 12 cm/ns, corresponding to a relative dielectric permittivity ranging from 19.62 to 6.25.

GPR data were acquired in two selected areas with a Ris-Hi mode system equipped with a double couple of antennas with central frequency at 200 and 600 MHz.

In the first area located in Cafetal (A, Fig. 9; see also Fig. 10) GPR data were acquired directly on the looting in order to verifying the presence of archaeological remains. Due to the objective difficult related to the irregular excavations (Fig. 10a) present in the area only two profiles were acquired (Fig. 10b). The data have been zero-timed, spatially filtered by a background removal and migrated in time domain. The processing has been performed by means of the Reflexw software (Sandmeier, 2011). Some gain vs. the depth has been applied too, but without meaningful results. Last but not least, after the processing the image has been corrected according to the topography of the surface that, of course is not flat because the prospecting follows the residual excavation (and soil deposit) profile left by the huajeros.

This poses a theoretical problem about the correctness of the processing, because some operations (in particular the migration) presuppose a flat interface. However, the average curvature ray of the hole is quite large with respect the central wavelength and this
makes us reasonably confident about the fact that an “usual” GPR processing is licit also in the cases at hand. However, the final topographic correction drove us to change the interpretation of some of the focused anomalies. In particular, in Figs. 11 and 12 we show the achieved results.

In both images Figs. 11a and 12a refers to the result achieved without topographic correction and Figs. 11b and 12b refers to the result after topographic correction. The topography has been manually measured with the spatial step of one metre, because we didn’t have at disposal more refined instruments at the moment of the measure.

The GPR profiles that were measured in the area show different reflectors with clear continuity along the two acquired profiles (Fig. 11 e 12). A hyperbolic shaped reflection labelled “A” at two-
way travel time window between 10 and 30 ns is visible in radar sections. Its size is about 0.5 m and the depth of the top is between 0.4 and 1.2 m (with an average electromagnetic wave velocity of 10 cm/ns).

Even so, the topographic correction revealed to be essential in order to reduce the “false alarm ratio”. In particular, in Figs. 11a and 12a the anomaly labelled “A” might be interpreted as buried targets from the non-corrected profile. However, the topographic correction reveals that they are quite probably just related to the curved stratification of the excavated area (Figs. 11b and 12b).

Unfortunately the acquisition of just two GPR profiles allows, only, to create a pseudo 3D visualization of the acquired data. In fact, data were displayed in a cube in which they appear in the position where they were acquired (Fig. 13). This allows to understand the development in a 3D way of the anomaly highlighted in the 2D profiles.

Another aspect appreciable at this stage is the level of the apparent maximum excavation depth. For example, in Fig. 12b seems that the maximum excavated depth has reached the time depth of about 1.2 m below the soil level. However, these aspects deserve further investigations: in particular, we don’t know precisely whether the clandestine excavations really leave a trace up to their original maximum depth (as it would surely happen e.g. in most cases in Europe) in or if the sandy-soil tends to re-compact again making indistinguishable the excavated from the non-excavated parts after some time (in its turn to be quantified).

In the second area located in Arenal (B1, Fig. 9; see also Fig. 14) the GPR prospecting was carried out near an abusive excavation in...
order to verify the existence of archaeological feature that could be preserved. Data were acquired in continuous mode along 0.5 m spaced survey lines, using 512 samples per trace, 80 ns time range and a manual time-varying gain function.

The data were subsequently processed using standard two-dimensional processing techniques by means of the GPR-Slice 7.0 software (Goodman, 2013). The processing flow-chart consists of the following steps: i) header editing for inserting the geometrical information; ii) frequency filtering; iii) manual gain, to adjust the acquisition gain function and enhance the visibility of deeper anomalies; iv) customized background removal to attenuate the horizontal banding in the deeper part of the sections (ringing), performed by subtracting in different time ranges a ‘local’ average noise trace estimated from suitably selected time-distance windows with low signal content (this local subtraction procedure was...
necessary to avoid artefacts created by the classic subtraction of a 'global' average trace estimated from the entire section, due to the presence of zones with a very strong signal; v) estimation of the average electromagnetic wave velocity by hyperbola fitting; vi) Kirchhoff migration, using a constant average velocity value of 10 cm/ns. The migrated data were subsequently merged together into three-dimensional volumes and visualized in various ways in order to enhance the spatial correlations of anomalies of interest.

A way to obtain visually useful maps for understanding the plan distribution of reflection amplitudes within specific time intervals is the creation of horizontal time slices. There are maps on which the reflection amplitudes have been projected at specified time (or depth), with a selected time interval (Conyers, 2006). In a graphic method developed by Goodman et al. (2006), named “overlay analysis”, the strongest and weakest reflectors at the depth of each slice are assigned specific colours. This technique allows the linkage of structures buried at different depths. This represents an improvement in imaging because subtle features that are indistinguishable on radargrams can be seen and interpreted in a more easy manner. In the present work the time slice technique has been used to display the amplitude variations within consecutive time windows of width $\Delta t = 5$ ns.

Moreover the highest amplitudes were rendered into an iso-surface (Conyers, 2004, Conyers, 2012; Conyers et al., 2013). 3D amplitude isosurface rendering displays amplitudes of equal value in the GPR study volume. Shading is usually used to illuminate these surfaces, giving the appearance of real archaeological structures. In this case the threshold calibration is a very delicate task in order to obtain useful results.

In order to define the depth of archaeological remains the EM wave velocity, using the characteristic hyperbolic shape of a reflection from a point source (diffraction hyperbola), was used.

Fig. 15 shows the processed radargram related to the second profile. It shows several hyperbolic shaped reflections labelled “A”
at two-way travel time window between 10 and 30 ns. Its size is about 0.5 m and the depth is between 0.5 and 1.17 m (with an average electromagnetic wave velocity of 7.8 cm/ns).

On each of the GPR records the lowest (dashed yellow labelled “S”) continuous and slightly undulating reflector appears strong and irregular reaching a maximum depth below the ground surface ranging from 1.1 to 1.3 m.

In order to identify the depth evolution of buried structures, including their size, shape and location, time slices using the overlay analysis (Goodman et al., 2006; Goodman and Piro, 2013) were built (Fig. 16). The time slices show the normalized amplitude using a range that defines the blue colour as the zero level and red colour as 1 level.

In the slices ranging from 54 cm to 128 cm depth, relatively high amplitude alignments (labelled A) are clearly visible. These correspond to the anomalies labelled A in radargram (Fig. 15). In the time slices (Fig. 16) ranging from 122 cm to 271 cm depth the high amplitude anomaly (labelled S) is clearly visible.

The anomalies highlighted by GPR measurements are probably related to some structures. In particular, the anomalies labelled A can be related to the adobe walls, while the anomaly labelled S is probably related to the ancient living surface.

Archaeological interpretation of GPR measurements can be favoured by displaying the acquired data set acquired with iso-amplitude surfaces (Fig. 17) (Conyers, 2004). A relatively strong continuous reflections are visible on the threshold volumes. This visualization technique put better in evidence the anomalies found in the surveyed area. In this case is clearly visible the 3D development of the anomalies labelled “A” and “S” respectively.

4. Final remarks

The plundering of archaeological sites, fed by illicit trade of antiquities, affects cultural heritage and, mainly, causes irreversible losses of knowledge about the human past. Even the finding of pillaged artefacts can not give back the cultural context information, lost forever by the pillaging of ‘huajeros’.

In the last decades the international cooperation among cultural organizations and museums proved to be effective in preventing illicit import and export of artefacts. However, the global dimension of the problem makes necessary further means and strategies to face the plundering of cultural sites in situ. To this aim, remote sensing can be a useful tool to quantify the damage and to support mitigation strategies.

This paper showed the results of a methodological approach proposed and tested for an archaeological area in Northern Peru strongly affected by looting still today.

We devised an automatic satellite data processing procedure to enhance and easier identify spatial patterns linked to looting of tombs. The analysis was performed by using VHR satellite imagery which enabled us to ascertain, quantify and map illegal excavations over time.

From the methodological point of view we adopted geostatistic approach based on LISA to clusterize patterns of circular holes which were automatically recognized using Kmeans classification.

Finally, georadar method has been applied to verify its capability in detecting anomalies of possible archaeological interest even in areas devastated by grave robbers. The results obtained from georadar are promising, and clearly show that the topographic correction is essential to reduce the “false alarm ratio”.

The encouraging results obtained in Peru clearly suggest that the use of satellite imagery can be very usefully applied not only to quantify (from time to time) but also to monitor (on a regular time basis) the most important archaeological areas especially for those located in desert and arid regions. Moreover, the integrated use of diverse remote sensing data sources from both active and passive sensors may provide a rich data set to support institutional authorities in the arrangement of mitigation strategies.

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