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Finding common ground: human and computer vision in archaeological prospection

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1. Introduction

The (slow) emergence of semi-automated or supervised detection techniques to identify anthropogenic objects in archaeological prospection using remote sensing data has received a mixed reception during the past decade. Critics have stressed the superiority of human vision and the irreplaceability of human judgement in recognising archaeological traces, perceiving a threat that will undermine professional expertise and that archaeological experience and knowledge could be written out of the interpretative process (e.g. Hanson 2008, 2010; Palmer & Cowley 2010; Parcak 2009). Uneasiness amongst some archaeologists of losing control, even partially, of the interpretation process certainly seems to be a significant factor in criticisms, citing the undeniable fact that archaeological remains (or proxies for those remains) can assume a near-unlimited assortment of shapes, sizes and spectral properties. It is argued that only the human observer can deal with such complexity. Thus, while increasingly automated and supervised procedures for object detection and recognition and processing are flourishing in a variety of fields (e.g. medical imaging, facial recognition, cartography, navigation, surveillance; Szeliski 2011), their application to archaeological and, more generally, cultural landscapes is still in its infancy. However, as a number of published works (see References and General Reading List) and ongoing research demonstrate there are major benefits in developing this broad agenda.

This paper provides a general review of the issues from a synergistic rather than competitive perspective, highlighting opportunities and discussing challenges. It also summarises a session on *Computer vision vs human perception in remote sensing image analysis: time to move on* held at the 44th Computer Applications and Quantitative Methods in Archaeology Conference (CAA 2016 Oslo 'Exploring Oceans of Data') that had a similar objective.

1.1 Some background

Aspects of image processing and 'automated' object detection were mainly introduced to aerial and remote sensing archaeology by satellite specialists (e.g. Shennan & Donoghue 1992), who draw on a long history of heavy image processing (e.g. Vegetation Indices, Tasselled-cap transformation, Pan Sharpening etc.). It is fair to say that sometimes archaeologically naive applications or interpretations fostered a hostile reception by some archaeologists, perhaps contributing to the often slow development towards mutual understanding. The archaeological naivety of some applications fed concerns that archaeological experience and knowledge, and the cognitive/perceptual ability of the archaeologist, were not being valued. Palmer and Cowley (2010) articulated some of these fears, writing that '...interpretation of aerial images is a specialist skill, improved by experience and ... methods of auto-extraction .... are a poor substitute for this.' These types of concerns are further expressed in Parcak's book on *Satellite Remote Sensing for Archaeology*, in which she states that '… computers simply do not have the same ability as human eyes to pick out subtleties...' and that '… only the viewer will know what he or she is looking for.' She also asks the question 'Why does there even need to be an automated process for satellite archaeology?' (Parcak 2009, 110-1).

These concerns and questions are addressed below, but in general it is fair to say that the debate has gradually moved on, underpinned by growing mutual understanding between different specialists and supported by the increasing ubiquity and power of computer vision techniques in complex fields such as medical imaging. While that is the case, such developments will not, by themselves, guarantee progress in aerial and remote sensing archaeology. There remain tensions and suspicion amongst some traditional practitioners, in part at least driven by a tendency to over-simplify issues, often from misunderstandings of workflows and processes. So, 'automation', as a rather ambiguous concept, can be still perceived as a threat to traditional practice. This may be reinforced by an unwillingness on the part of some archaeological practitioners to reflect critically on how they 'look and see' and to critique how appropriate established means of observation are to large complex datasets such as large area Airborne Laser Scanning (ALS) coverage or multispectral data (Cowley 2012).

This reflection can be assisted by a review of current research on (semi-)automated archaeological object detection as provided below, as this may at the same time shed light on some aspects of traditional practice. There are bigger questions too, such as how to create datasets that can inform heritage management in parts of the world that are either inaccessible (e.g. war zones), for which base data such as maps or aerial images is difficult to acquire (e.g. due to legal restrictions), or that have no tradition of creating archaeological inventories. At the heart of all these issues is the question of how well routine practice developed during the 20th century is equipped to address the complexity and scale of emergent data now available in the 21st century.

1.2 Defining some terms of reference

It may be unnecessary to state that no one advocates 'automatic archaeology', but it is worth asserting here because the study of the human past through material remains is not something that can be automated – it is an endeavour made up of many processes and approaches in which the emotions and intellect of the archaeologist play a central role (Barceló 2008). Amongst these processes is the examination of material remains directly, and through various proxies (e.g. aerial photographs), in order to identify attributes, features and objects that may be fed into interpretative frameworks. Aerial and remote sensing archaeology draws heavily on imagery (photographs, spectral imaging) and digital topographic data (ALS, radar) for the identification of attributes, features and objects. In a traditional or manual approach this may involve the examination of photographs of a field, identifying a variation in the crop that is interpreted as a ditch and further as the ploughed down buried remains of the perimeter of a Roman Marching Camp (Fig. 1). There are a number of processes at work here – in the examination of imagery, the identification of features or objects that are of interest, and their interpretation and mapping as material remains of the past, and it is the processing and examination of imagery, and the detection/recognition of features or objects that are of potential interest that we think is the most productive area for the development of 'automated', semi-automated or computational approaches. The interpretation and validation of objects extracted from imagery or other data remains the prerogative of the archaeologist.

Fig. 1 - Differential cropmarking shows the buried ditch of a Roman Marching Camp and the remains of Iron Age settlement at Dun in eastern Scotland. Manual (human observer led) examination of this image might draw on knowledge of crop response, observed morphology and analogous sites (from excavation and survey data) to identify what is of interest, to map them and generate an interpretation. The more explicit the assumptions on which such processes are based the more reliable the outputs, and this too is the case for heavily automated approaches identifying objects of potential interest in such data. (DP166954 © Historic Environment Scotland)

In practice, especially in manual workflows, the components (i.e. detection, recognition and mapping, classification and interpretation) of workflows are often intermixed, but, regardless of whether or not this is best practice, it helps clarity to compartmentalise them (Fig. 2).

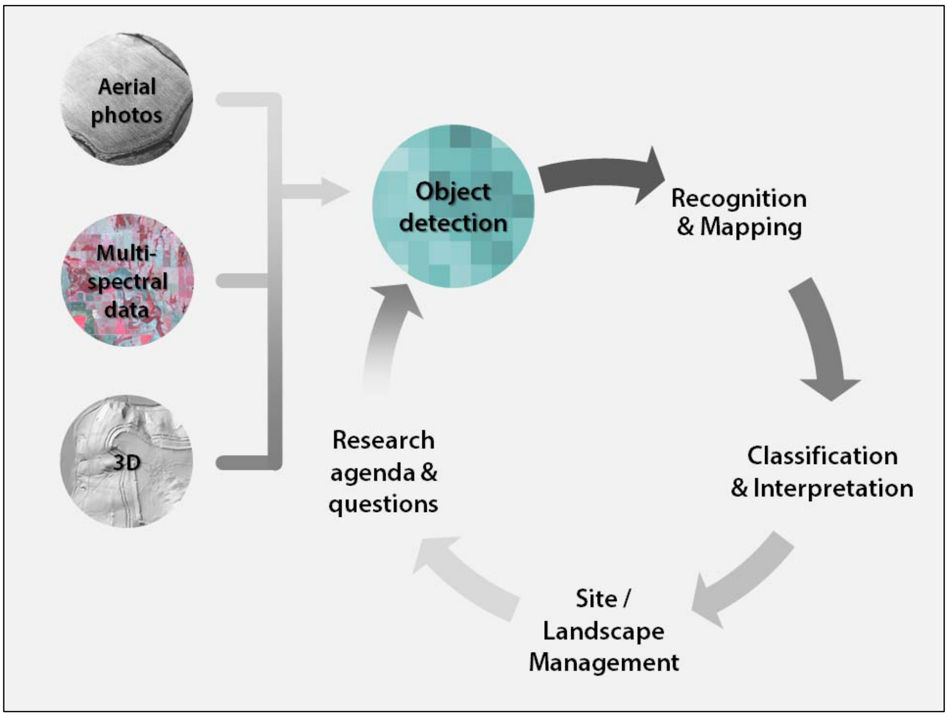

Fig. 2 - The object detection and interpretation process. This stresses the iterative nature of the processes and the focus of current work on automation in object detection. (Graphic A. Traviglia).

There is probably a general consensus amongst advocates of increasingly computational approaches drawing on computer vision and – in time – artificial intelligence, that one of their strengths lies in the examination of imagery/data to identify elements that conform to a defined set of characteristics (i.e. a model) and to extract those objects or patterns. Another area of consensus is that quick, systematic and consistent processing of large and complex image datasets is absolutely vital to facilitate exploration of the data and assist interpretation. What is not being claimed is any particular role in the subsequent archaeological interpretation – which is where the experience, knowledge and imagination of the archaeologist are paramount.

1.3 Defining some terminology

The topic under discussion here is cross-disciplinary and that brings with it a need to ensure terminology is used explicitly so that dialogue is constructive and mutually understood. In this paper we will use terminology from computer vision as this benefits from explicit definition, in a way that equivalent archaeological usage often does not. Firstly, we aim to avoid the use of 'archaeological feature'. Although it is a common term in archaeology, it is often used, like 'anomaly', in a vague and ambiguous way for things we do not specify further – sometimes because we cannot, but often because we are lazy. Such a use of the term is not common in computer vision, where 'features' are first of all image properties that may have real-world correlates, but very often do not. In computer vision, feature detection usually happens in an early stage of image processing, for example in finding suitable points for image matching. When it comes to real-world entities – and that is what we as archaeologists want to find in remote sensing data – computer vision refers to them as 'objects' and we will be using this definition forthwith. Object detection is a much later step in the workflow than feature detection (Szeliski 2011), and this is the step that is a central focus of archaeological applications and potential.

1.4 Towards common ground

It will come as no surprise to the reader that the authors of this paper are advocates of exploring the applications of supervised and increasingly automated object detection in archaeology. They have incorporated such approaches in their own work (Lambers & Zingman 2013, Zingman *et al.* 2016), given papers, organised conference sessions and written about issues and interfaces with other fields of archaeological practice (Cowley 2012, 2013; Opitz & Cowley 2013; Bennett *et al.* 2014). In this, they share the views of a growing number of practitioners who increasingly see the power of fields like computer vision and other methods for object detection (e.g. Trier *et al*. 2015; Sevara *et al.* 2016). Crucially they see this as a world of opportunity, not a threat, recognising that there is an interesting future in developing thoughtful approaches, and addressing challenges to workflows and routine practice. In particular, this applies to tackling large area and complex data for which traditional observer-based 'looking' is slow, and probably not especially suited to seeing differently (cf. the issues of confirmation bias). The many (new) ways of seeing that are offered by computer vision or analysis of topographic data have the potential to create a strong iterative relationship with traditional techniques, and for the experienced observer, of aerial photographs for example, should represent a world of opportunity for self-exploration that extends beyond simply relying on the eye and cognitive powers. Such issues lie at the core of developing 21st century solutions to 21st century problems, rather than uncritically taking techniques developed in the 20th century and insisting they will maintain a currency for evermore. We believe that this basic position is strongly borne out by the papers presented at the CAA 2016 session that is summarised below by way of illustration.

2. Finding common ground – CAA 2016 session summary

The CAA 2016 session '*Computer vision vs human perception in remote sensing image analysis: Time to move on*' organised by Arianna Traviglia and Karsten Lambers was underpinned by a basic premise that the time to move on from polarised discussion is well overdue. That is to say that the focus for discussion should now move firmly to 'how', rather than 'if' computational approaches to detection and extraction are applied in remote sensing archaeology. In many ways the 2016 Oslo session was a follow-up to a similar session held at CAA 2009 in Williamsburg and summarised in *AARGnews* 39 (De Laet & Lambers 2009). Papers in that session demonstrated the state of the art of remote sensing archaeology and called for increased collaboration and understanding between aerial archaeologists and remote sensing specialists. Even in 2009, while 'automation' was still a new topic, the session conveners concluded that the 'uncooperative' nature of archaeological remains '… does not mean that semi-automated detection approaches are doomed to fail from the outset' (De Laet & Lambers 2009, 13).

The contributions to the CAA 2016 session certainly confirm that this optimism was justified, with significant progress in many areas over less than a decade. A notable characteristic of the 2016 session is a focus on ALS data, reflecting the proliferation of archaeological applications over the last decade. However, it also became clear that many computational techniques can be applied across a range of different data, from optical images to geophysical measurements and ALS-derived DEMS, or combinations of these data sources.

The CAA session invited presentations on computer vision methods that are being used or developed to automatically identify landscape patterns and/or objects from remote sensing data and imagery. While the organisers were open to papers critiquing the topic, perhaps unsurprisingly for a CAA conference, presentations and the audience broadly shared a basic premise that automation demands to be explored as a basic and routine element of archaeological practice. The brief summaries of papers below illustrate how researchers are trying to automate parts of the workflow for archaeological object detection employing a variety of approaches, from innovative combinations of simple image processing tools to sophisticated handcrafted detection algorithms and further to high-level computational approaches, such as deep learning.[1]

The session was opened with a paper by **Dave Cowley**, **Arianna Traviglia** and **Karsten Lambers**, entitled *Why, when and how? Context and computer vision in archaeological prospection and interpretation*. This introductory presentation provided background to current issues and polarisations around automation in archaeological prospection. A central theme was the lack of explicitness about how archaeological object identification is undertaken and how the processes, whether 'automated' or 'human', of identifying patterns, shapes and objects interrelate with archaeological interpretation, providing a framework for critical discussion of the relationships between emergent approaches and traditional skills. The paper covered many of the issues presented above, addressing questions related to: how can we

[1] A selection of papers from the CAA conference in Oslo, edited by E. Uleberg and M. Matsumoto, will be published about one year after the event. See the conference website (CAA 2016) for information on the proceedings.

create clarity about why and when automated approaches are desirable; what are the roles of (traditional/manual) archaeological experience and skills in designing algorithms; and how can automated/manual approaches be used iteratively to improve archaeological detection – questions that were, at least partially, addressed by the following papers, summarised here not in the order of presentation but according to the increasing sophistication of tools / decreasing level of user interaction.

Benjamin Stular (Research Centre of the Slovenian Academy of Sciences and Arts, Ljubljana) presented a paper on *Two methods for semi-automated feature extraction from Lidar-derived DEM designed for cairn-fields and burial mounds* that illustrated the potential of simple and easily applied techniques for semi-automated detection of specific monument types that share a basic morphology. In aiming to detect objects that survive in the surface topography as mounds, two methods were applied, both of which were implemented in free GIS software packages. The first used the standard deviation of elevation-based local relief and subsequent classification of 2D shapes, while the second method used a peak (i.e. highest point) finding algorithm. Both methods were tested in two different case studies that provided not only 'ideal' conditions but also a very demanding one. Although decent accuracy of mapping compared to manual interpretation was achieved, the method was recommended as a mapping (vectorising) tool rather than an interpretation tool.

In his paper on *Experiments in the automatic detection of archaeological features in remotely sensed data from Great Plains USA villages*, **Kenneth L Kvamme** (University of Arkansas) also explored how relatively common GIS tools can be employed for the identification of specific archaeological object types. Using case study survey data of prehistoric villages associated with native farming tribes of the Great Plains (USA), which incorporates ground-based geophysics and aerial remote sensing including ALS, a variety of methods were applied that collectively offer a diverse array of decision-making mechanisms for the identification and classification of complex archaeological objects. Image manipulation tools (e.g. Low- and High-pass filters) were used during pre-processing to simplify noisy data and remove local geological or topographical trends, while Fourier methods isolated and removed elements such as plough marks that may obscure the archaeological signal. Reclassification tools were used to define anomalous or potential anthropogenic objects. Shape indices were applied to allow objects to be characterised and scaled, and the use of 'distance' modules supported consideration of context, while custom filters may be designed to recognise complex shapes through pattern matching approaches (Fig. 3).

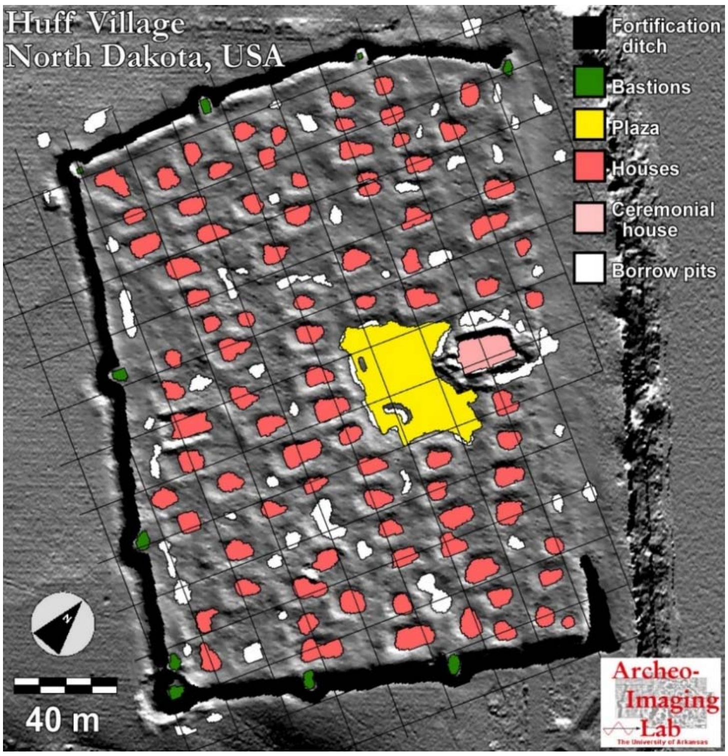

Fig.3 - Automatic classification results derived from the bare earth elevation data at Huff Village. (Image courtesy of K. Kvamme).

With the following papers the emphasis shifts to increasingly heavy computational demands, beginning with a paper by **Amandine Robin** and **Karim Sadr** (University of the Witwatersrand) on *Automated detection of stone-walled ruins based on support vector machine and histogram of oriented gradients*. They propose an autonomous approach to detect ruins based on Histograms of Oriented Gradients for object extraction and on a Support Vector Machine in order to classify extracted objects as 'ruin' and 'non-ruin'. The support vector machine uses a training set of previously identified structures to learn to distinguish ruins, and was then applied to a subset of locations within a 9000 km^2 study area in the southern Gauteng Province of South Africa, to automatically identify pre-colonial stone-walled structures without any *a priori* knowledge. These structures are very subtle and made from locally available material. Shapes are diverse and tend to be occluded by vegetation, and are therefore difficult to differentiate from natural landforms and flora. The study used satellite images (from Google Earth), aerial photos and ALS DTMs and achieved a relatively high level of accuracy and control of false detections.

Till Sonnemann (Leiden University) and his co-authors **Jessie Leigh Pasolic**, **Douglas Comer, William Megarry**, **Bryce Davenport**, and **Eduardo Herrera Malatesta** presented a paper titled *Down to the last pixel: Multiband use for direct detection of Caribbean indigenous archaeology*, exploring the utility of satellite imagery and radar data for detecting pre-colonial settlement remains. These comprise slight topographic modifications, house platforms and small mounds predominantly of midden and soil that also include ceramics and lithic assemblages. The altered topography and the surface scatters were used as quantifiable indicators of an archaeological site. Using pixel information from known sample sites and areas with no known archaeological evidence, a combination of multispectral bands (Worldview-2, Aster, LandSAT) and SAR (UAVSAR L-band, TanDEM-X) was used to feed a direct detection algorithm developed at Cultural Site Research and Management (CSRM) and Johns Hopkins University that assesses the probability of the presence of sites comparing means of similar pixel values within each data set. The pre-processed very diverse data sets had to be exactly matched in resolution and location, feeding a semi-automatic process that requires supercomputing. The output maps, combining all data sets through Boolean merge, present quantifiable statistical results of areas with similar pixel values to the known sites, defining areas of high or low probability of archaeological evidence.

Iris Kramer (University of Southampton) presented a paper on *Using eCognition to improve feature recognition* inspired by successful applications in Geosciences for dealing with supervised classification of irregular landforms, such as landslides. This approach draws on the image analysis software TRIMBLE eCognition that implements geographical object-based image analysis (GeOBIA), a programme that has been applied to a limited degree in archaeology. This paper highlighted new additions to the array of already available methods to re-evaluate what the potential is for object recognition: for instance, the integration of ALS data and aerial photographs, which has always been sought-after, as well as the ability to transfer rule sets modelling target objects for the detection of common features, a feature that can facilitate data and knowledge-sharing amongst researchers.

The case study presented three different automated detection methods: the well-known eCognition rule set generation based on cognitive reasoning; self-learning algorithms; and adaptive template matching. These techniques were applied to round barrow detection in the Avebury region of southern England, specifically distinguishing between the known variations of barrow, bank and ditch (Fig. 4). The algorithms were intended to prioritise cognitive aspects of human vision such as elevation, size, shape and texture, using ALS data and aerial photographs.

This paper was the winner of the Nick Ryan Bursary award for best student paper at the CAA conference, and is based on a Masters thesis (Kramer 2015).

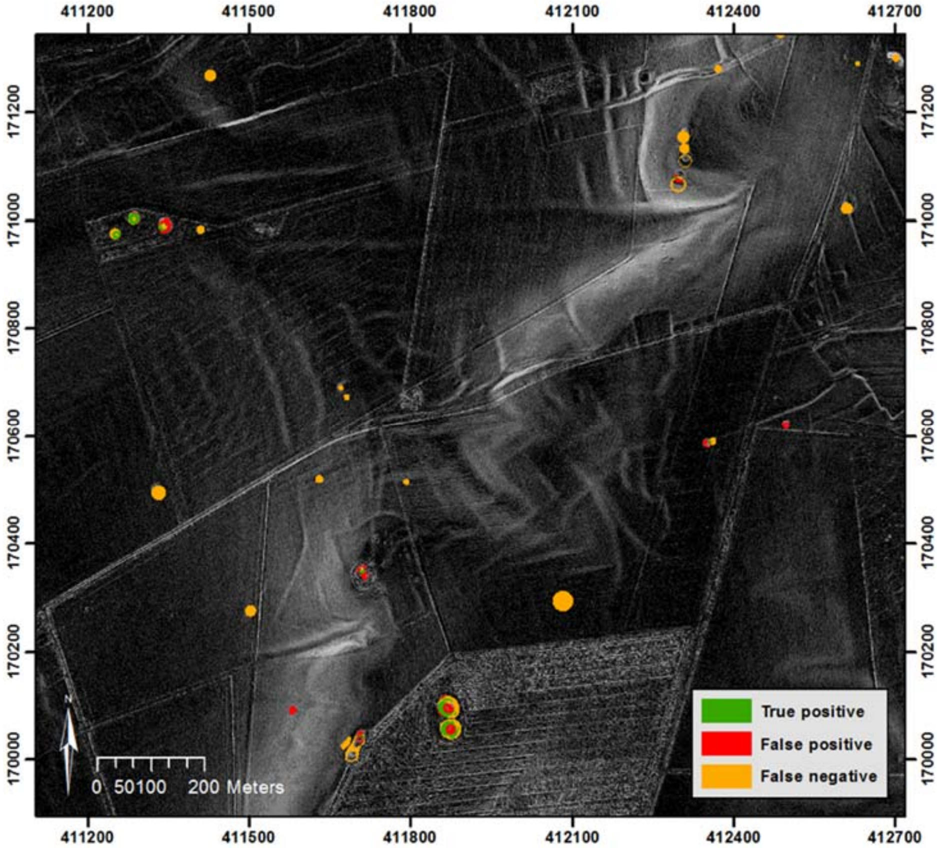

Fig. 4 - Map of results from a case study east of Windmill Hill and north of Overton Hill. The 'true positive' (green) show agreement between the automated detection and known (from other methods) barrows, while the 'false positive' (red) indicate sites that are wrongly identified by the automated routines. The 'false negative' (yellow) returns are known barrows that were not detected using the automated routines. (Image courtesy of I. Kramer).

Norwegian researchers have been at the forefront in the development of automated detection for many years (Trier *et al.* 2009), and the paper by **Øivind Due Trier**, **Arnt-Børre Salberg**, and **Lars Holger Pilø** (Norwegian Computing Center, Oslo) on *Semi-automatic detection of charcoal kilns from airborne laser scanning data – by using deep learning* presented their recent advances. This work demonstrated the potential of new high-end methods for the semi-automatic detection of charcoal kilns in ALS data. The establishment of a number of iron works in Norway during the 17th century required large amounts of charcoal, and past archaeological surveys have pointed to the presence of large numbers of charcoal kilns, but it was not known how many kilns there were, if they showed signs of reuse, and how they were distributed across the landscape. This case study used ALS data for the entire forested valley in Lesja, Oppland County. Initial visual interpretation of the dataset in the central area identified about 1000 possible round charcoal kilns, varying in diameter from 10 to 20 m. Beyond some basic similarities, the kilns exhibited a variety of forms, including the presence of a surrounding ditch and of pits and low mounds. While previous studies by the same authors used sophisticated hand-crafted algorithms for object detection, in this study the authors adapted and applied a generic machine learning approach based on deep convolutional neural networks (CNN). CNNs are multi-layered networks of artificial neurons that emulate the biological visual cortex and, like humans and animals, learn from training examples. They have recently gained recognition for dramatically improving previous success rates in object detection (Krizhevsky *et al.* 2012; LeCun *et al.* 2015) and can be adapted to specific tasks by introducing case-specific classifiers on the deepest layer. In this study the classifier was constructed from image patches of charcoal kilns in ALS data identified by visual interpretation. The yes/no classifier for kiln detection was then applied to the ALS data in a moving window. Initial results over a 3 km by 3 km test area yielded a remarkable 85% rate of true detections (Fig. 5).

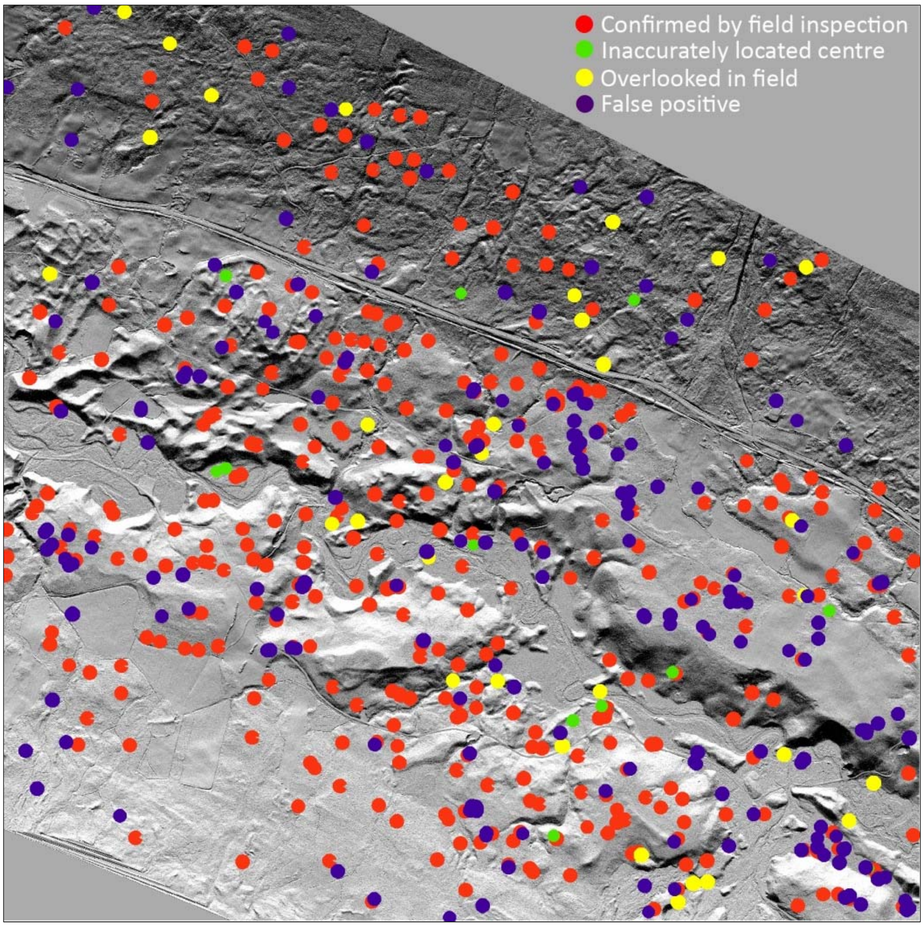

Fig. 5 - Result of automatic charcoal kiln detection for a 3 km × 3 km test area. This illustrates the high return of positive identifications, including those that were overlooked during field investigation, set against the false positives from the automatic detection. (Image courtesy of Ø. Trier).

The importance of the Norwegian case study is not just that, along with Zingman *et al.* (2016), this is the first application of new and highly promising CNN-based machine learning approaches to archaeological prospection, but also its effect on archaeological practice. In a complementary paper by **Martin Kermit** and **Øivind Due Trier**, entitled *Towards a national infrastructure for semi-automated mapping of cultural heritage in Norway* and presented in another CAA session, the authors demonstrated a new web portal for heritage professionals in Norway in which the semi-automated detection tools for different kinds of archaeological remains developed over the last decade are implemented in an intuitive and easy-to-use environment. For the first time, this web portal will make advanced detection tools available for the daily business of heritage management.

While much of the work on automating detection has used satellite data and ALS, the presentation by **Sebastian Zambanini**, **Fabian Hollaus** and **Robert Sablatnig** (TU Wien) on *Computer vision applied to historical air photos: The registration and object detection challenge* reminded us of the importance of collections of historic aerial photographs. This work forms part of the DeVisOR project (Computer Vision Lab 2016), and addressed the issues of automatically analysing aerial photographs taken during World War II air strikes to locate unexploded ordnance (UXOs) and to detect military objects (e.g. bomb craters or trenches). In an issue shared with the Sonnemann *et al.* paper, registration of data to common standards is a challenge (Fig. 6), as changes in imagery since printing (e.g. warping) and in the landscape (urban and rural development) make point matching and sample-based transformations difficult, further exacerbated by the generally low quality of the old aerial photographs and variations caused by illumination, for example. These problems are also manifest in the detection stage, which is further impeded by the absence of large training sets. While no solutions were offered, this work in progress identified the potential dividend from tackling these issues with less than ideal datasets, that never-the-less hold unique information.

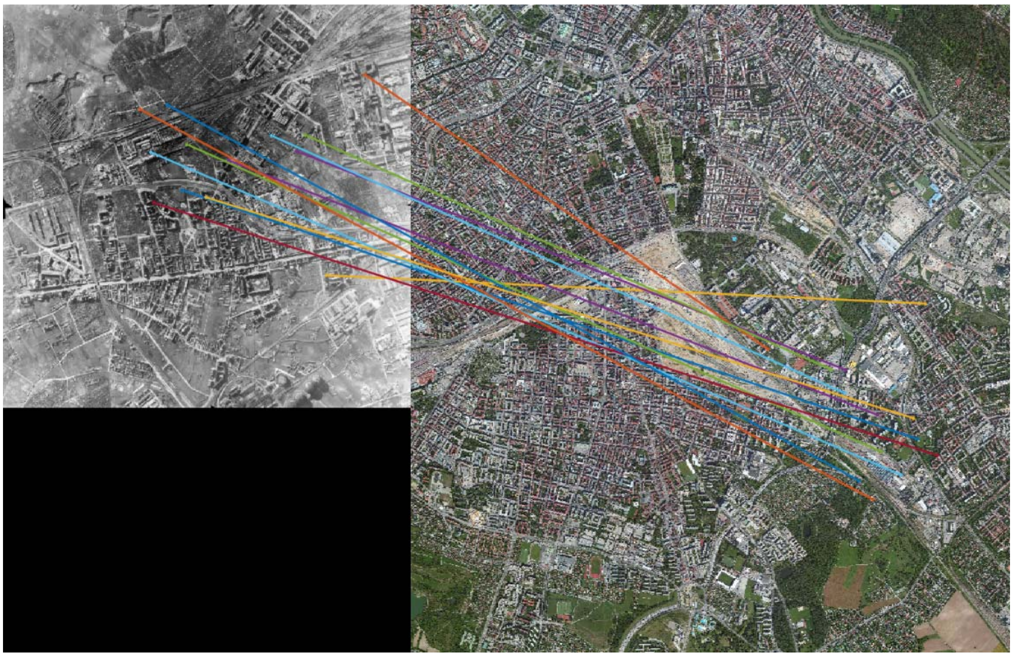

Fig. 6 - Correspondences of one image pair. The left image is the historical aerial photo and that on the right a modern satellite image. (Image courtesy of S. Zambanini).

3 On common ground? Observations on the CAA session

The CAA session brought together a diverse range of papers, presenting work from a wide variety of contexts that make use of a broad range of methods. One key point to emerge is that there is increasing acceptance that supervised and heavily automated detection routines are becoming less contentious in many areas of archaeological practice. Indeed, this point was brought out in a paper by **Karl Hjalte Maack Raun** and **Duncan Paterson** presented in another session at CAA on a *Systematic Literature Review on Automated Monument Detection - A remote investigation on patterns within the field of automated monument detection*. This study documented the proliferation of automated procedures by correlating key terms for ALS and remote sensing data with academic citations of their use. Results were explored using network analysis to investigate the personal, institutional and financial connections and actors involved in automated monument detection, documenting the evolution of 'automated monument detection' for ALS and remote sensing data from 2000 to 2015. Not surprisingly, the study demonstrates that well-known key papers such as those by De Laet *et al.* (2007) and Menze and Ur (2007) helped to introduce concepts of automation to the archaeological community.

This is an encouraging trend – and a healthy one if the papers presented at CAA 2016 are a good measure. The common ground with fields such as computer vision is clear, while the connections that are being maintained with aspects of field practice are encouraging. The iterative engagement of automated/supervised detection and 'traditional' observation should be highly productive – each offering the potential to improve the other without opposition. So too is the increasingly explicit statement of workflow and process that helps practitioners understand where and how particular methods or processes take place. And, while some approaches clearly demand access to expensive resources and specialist input, there are tools available to all (e.g. in Open Source GIS software) that allow the user to think about how they define objects and sites as explicitly as possible – which can only be a good thing – and how they might implement those definitions in routine software.

After all, surely the important point about the detection of objects of interest is not whether it was undertaken by making heavy use of software, or through the services of a human observer, but that the processes and parameters of detection are explicit and systematic. If the detection process is undertaken using an explicit, systematic, automated approach that does not rely on an individual's perception, ability, attention or any other personal parameter, this only increases the probability of identification of relevant traces, creates an accountable and replicable process and has no reason to invalidate or undervalue the interpretative (human-driven) process that will follow. In addition, the automation of some steps within the object detection process enhances the opportunity for a remote sensing operator to improve their visual detection capabilities by highlighting marks, patterns, and features that might otherwise be overlooked, thus creating learning opportunities.

4 Conclusions and future perspectives

Having already clarified that we firmly believe that by now the matter for discussion is not 'if' such approaches are worthwhile, we should now move the discussion on to 'how' a variety of approaches now available should be incorporated in the archaeologist's toolkit. A discussion session held at the AARG annual conference during September 2016 in Plzeň on the topic of 'automation' addressed this issue through three papers: Dimitrij Mlekuz speaking on *From quantity to a new quality: Big Data and landscape archaeology*; Dave Cowley, Arianna Traviglia and Karsten Lambers speaking on *Finding common ground: Human and computer vision in archaeological prospection and interpretation*; and Toby Driver on *Shared goals: Using airborne imagery to develop landscape understanding (however we do it)*. In all papers the need to develop perspectives that allow us to engage with big data were stressed, identifying the desirability of active engagement in developing applications rather than retrenchment and opposition. These generated an active discussion, with broad agreement that dogmatic opposition was not desirable and a general recognition that such developments are positive.

There remains a necessity for critical reflection on what is being done to ensure that unthinking applications are not developed and that the theoretical and philosophical underpinnings of an evolving application of increasingly heavy computational approaches are explored. Recognising that archaeology is poorly funded and not well-placed to develop bespoke applications, there is a need to look closely at progress in other disciplines and to critically and carefully select what is relevant to our own field and can be translated into applications that improve our work (which will be the subject of a session at CAA 2017 in Atlanta). To do otherwise is to risk generating unthinking applications that generate poorly understood outputs. There is also a need to recognise that this is a very dynamic field with rapid developments in algorithms and computational power, and that while many first steps may be less productive than might be wished for, there is a bigger picture to keep an eye on: that of moving practice along in a dynamic environment (Opitz 2016).

To facilitate this process, as well as the references cited in the text, a (necessarily incomplete) reading list of papers on applications of automated detection and recognition procedures for a variety of airborne and satellite data is also included in this volume of *AARGnews* (Lambers and Traviglia 2016).

Acknowledgements

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