APPLICATION OF HOUGH FORESTS FOR THE DETECTION OF GRAVE MOUNDS IN HIGH-RESOLUTION SATELLITE IMAGERY

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ABSTRACT

The conditions in the Altai Mountains make it a difficult area for archaeological on-ground surveys. Automatic surveying could facilitate decision making and planning as well as the building of a comprehensive database of archaeological monuments. We have tried three different approaches towards automatic detection of grave mounds in high-resolution optical data and found an object-class specific Hough forest algorithm the most suitable for the purpose. Through adaption and testing of the algorithm on IKONOS-2 data we created a tool for mapping archaeological features in the Altai Mountains, hence contributing to future steps towards a sustainable cultural heritage management.

1. INTRODUCTION

The frozen tombs of Iron Age civilizations in the Altai Mountains are under threat. This unique cultural heritage and invaluable archaeological source being preserved for more than 2000 years runs the risk of ultimately being destroyed by climatic change i.e. the thawing of the permafrost [1]. However, fueled by technological progress in the areas of geophysical prospection and remote sensing the research of large-scale areas of interest has become economically feasible and advances our understanding of ancient cultures in ways that have not been possible before. Without being as time consuming and resource intensive as e.g. excavations campaigns are, preliminary satellite imagery based analysis of archaeological landscape is now an indispensable tool for understanding a site within its geographical context and a valuable decision basis for further on-ground research activities. In case of the Iron Age burial mounds in the Altai Mountains the limited accessibility of those mountainous regions and the scattered archaeological sites in a vast geographical context make a complete on-ground survey almost impossible. Although there have been comprehensive surveys in some areas of the Altai [2] such an approach is clearly limited by financial and temporal constraints.
The collection of data is generally the most time-consuming and resource-demanding step of archaeological projects, especially when conducting large-scale landscape archaeological analyses [3].
We have tried to establish an algorithm-based detection of Scythian grave mounds in order to tag areas of paramount importance for future intensive surveys and preservation measures.

2. ALGORITHM DEVELOPMENT

We tested three different approaches towards the problem of automatic detection of Scythian grave mounds in the Altai Mountains: First, we tried to make use of the circular characteristics of the archaeological features by searching areas with a potentially high density of archaeological sites for structures with an inherently circular shape. As a second approach, we applied SIFT-Features with large training samples in order to detect archaeological structures with a high degree of similarity. Finally, we implemented and tested class-specific Hough Forests for object detection.

2.1 Template Matching

This first approach has been tried before on high-resolution satellite data for cultural heritage purposes. It is relatively easy to implement, however, since the algorithm is completely unspecific, leading to a large number of false positive detections [4, 5]. Based on the approximate size of the archaeological features we can introduce limitations for the detection of Iron Age grave mounds. Inevitably there occur problems with oval structures and mounds which had been damaged by agricultural activities, natural erosion and looting or whose outline in the satellite data is changed by vegetation. Additionally recent anthropogenic structures like yurts, paddocks, and circularly irrigated fields as well as natural features like rock outcrops, ponds and large trees posed a problem for a fully automatic approach. Circular vegetation features and water surfaces can easily be eliminated from the search area, rock outcrops are too similar to the stone interspersed surface of tombs though. The algorithm can be used for a detection of areas with an overall high density of circular features. Specific detection of Iron Age mounds on the other hand is not possible. The high number of false positive detections renders time-consuming manual verifications necessary. This approach was hence dismissed as it did not fulfil our requirements for an efficient automatic detection of archaeological features.

2.2 SIFT-Features

The scale and rotation invariance of SIFT-Features as well as their robustness to changing lighting conditions and small divergences in view angle made them a promising choice at first [6]. Although extremely useful for robust image matching and retrieving known objects from a scene [7, 8] the algorithm was found to be too specific to deal with intra-class differences. This characteristic made it necessary to drastically increase the number of training images and to deal with a computationally highly intensive process. The SIFT-Algorithm, however, has another characteristic which makes it worth considering in cases where an area of interest is not completely covered by one type of data: The sophisticated descriptors make it possible to search different types of satellite imagery for archaeological features with the same set of training samples. In our case the approach was rejected because of the time-consuming preparation required for its application; it is not consistent with the request for an efficient object-class specific detection of archaeological features in the Altai Mountains.

2.3 Hough Forests

The Iron Age grave mounds vary considerably in size, vegetal cover, and condition of preservation, nonetheless they form a relatively uniform object class. These circumstances make their detection similar to other well-known challenges in computer vision like the detection of pedestrians or the counting of vehicles in video footage. Therefore, there are a number of well-documented methods available, which allow for a relatively quick adaption. We decided to work with class-specific Hough Forests because of their competitive performance with respect to the previous state-of-the-art methods [9].

Hough Forests are random forest used for the application of a Hough voting scheme for object detection [9]. In this scheme, training samples are divided into overlapping patches: Positive samples are part of the objects to be detected, negative samples are drawn from the background. With patches from positive samples and negative samples, the trees τ in the Hough Forest are constructed. More precisely, histograms of oriented gradients (HOG) features $\mathcal{F}$ of images are computed, then rigid patches are extracted from the images [10]. We denote the patches by $\{\mathcal{P}_i = (\mathcal{F}_i, c_i, d_i)\}$, where $\mathcal{P}_i$ is the patch, $_i$ is the index of the patch, and $\mathcal{F}_i$ is the HOG feature of the patch. c_i is the class label of the patch, $c_i = 0$ for patches from negative samples while $c_i = 0$ for patches from the positive samples. d_i is a vector denoting the offset of the patch from the center of the object in a positive sample. Obviously, d_i is undefined for patches from negative samples.

At training stage, all patches from the training database are extracted and a series of binary test is made to build the Hough trees τ. We rewrite the feature of the patch as $\mathcal{F}_i = (\mathcal{F}_i^1, \mathcal{F}_i^2, \ldots, \mathcal{F}_i^c)$ where ^{c} is the dimension of the HOG feature. Two positions (p, q) and (r, s) in the patch are selected randomly, as well as the feature channel $\alpha \in \{1, 2, \ldots, c\}$ and the handicap value ε. The binary test can be written as [8]:

$$\tau_{\alpha,p,q,r,s,\varepsilon}(\mathcal{P}) = \{\text{if } \mathcal{F}^{\alpha}(p, q) < \mathcal{F}^{\alpha}(r, s) + \varepsilon, 0, \text{otherwise}, 1\}$$

In each test, patches are divided into two fractions: The left child and the right child of the node. The classification rate of all tests is calculated, and the parameters (α, p, q, r, s, ε) of the best rates become the decision criterion of the current node. We repeat this step until the tree reaches its deepest level. The leaves of the trees contain the pure patches, which are used to cast a vote on the center of the object by means of their offset d_i. In this way N trees are constructed constituting the Hough forest.

At detection stage, a sliding window is applied to the remote sensing image. Small patches are extracted from the sliding window and classified by all trees; as each patch reaches the leaves of the trees, it votes for the center of the inferred object by the offset the node has stored. The areas with the highest densities of votes form detection hypotheses which are controlled by thresholding [9].

3. ADAPTION AND TESTING

The object-class specific Hough forest algorithm was adapted and tested on IKONOS-2 data of the Russian and Chinese Altai Mountains (see Fig.1). We randomly defined twelve areas one of which was used for training the others served as testing areas. At first we mapped all visible grave mounds in the data, then they were split into three categories: *Cat.I* encompassed clearly visible archaeological features with a strong contrast against the background and only minor aberrations in shape. *Cat.II* consisted of monuments which were well identifiable but changed through external influences like plowing or vegetation. *Cat.III* comprised all the mounds which were hardly visible due to low contrast against the background,

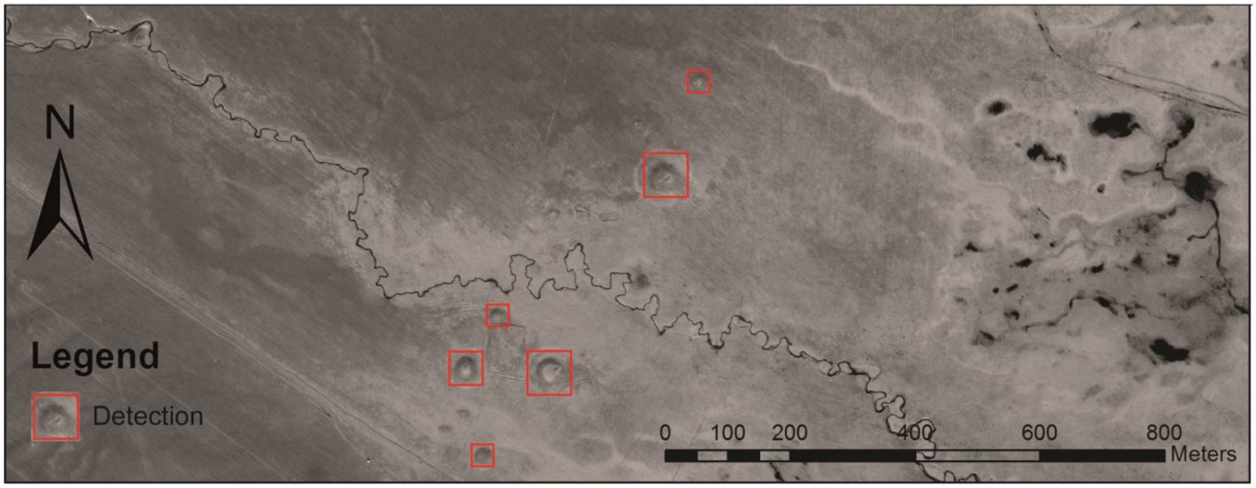

Figure 1. Detections of algorithm on IKONOS-2 data

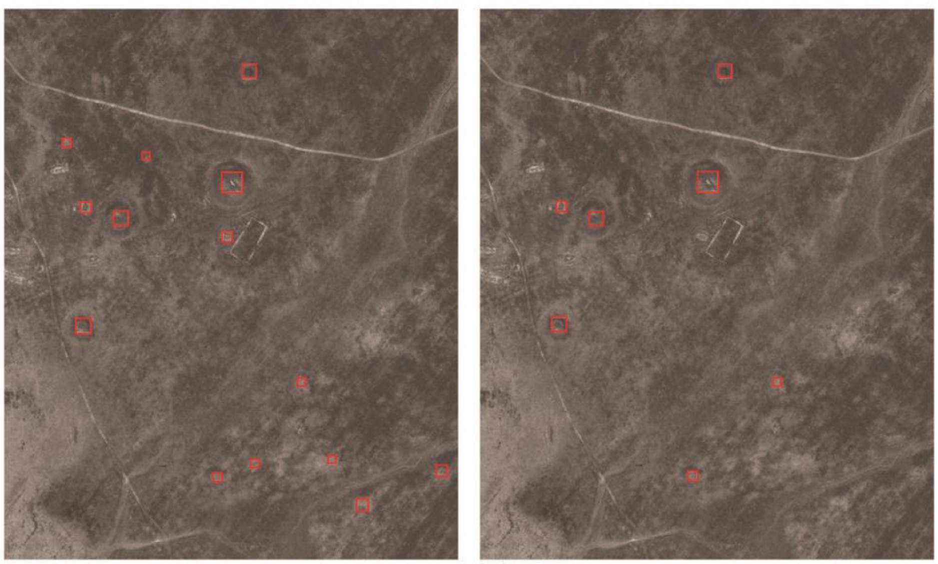

Figure 2. Control of false positive detections through thresholding (left threshold 1.65, right threshold 1.95)

completely lost their originally circular shape, or could only be identified through a looting pit.

Out of the archaeological features in Cat.I the algorithm detects a major part and seems to be relatively robust to changes in threshold value. Monuments of Cat.II are still detected at a reasonable rate, however, if aiming at higher detection rates in Cat.II the threshold has to be lowered and therefore the false positive detections increase much quicker (see Tab. I). Cat.III is not only virtually undetectable but, as further testing has shown, also decreases the robustness of the algorithm. Inclusion of Cat.III features in the training sample leads to more false positive detections.

TABLE I

TESTING RESULTS FOR RANDOM TRAINING SAMPLE

threshold	Cat.I	Cat.II	Cat.III	false pos.
optical	26	23	101	0
1.45	25	11	1	81
1.55	23	11	0	34
1.65	23	9	0	11
1.75	23	5	0	4

The control of false positive detections through thresholding is primarily a trade-off between the number of correct detections and the amount of time invested in verifying the results (see Fig.2). For truly large-scale surveys the number of false positive detections should be kept to a minimum.

4. OUTLOOK

With the achieved detection rates of up to 88% within the most visible category we would be able to conduct large scale automatic surveys of grave mounds in the region of the Altai Mountains using high-resolution optical data. In combination with on-ground GPS-based surveys we could hence generate a comprehensive data base for the purpose of cultural heritage management and the preservation of the invaluable source of knowledge those archaeological monuments represent. Such a data base would form an integral part of a proactive response to threats to the frozen tombs like the thawing of the permafrost and more direct anthropogenic influences like e.g. the construction of pipelines [11] or the touristic development throughout recent years [1]. Further analysis of site characteristics and distributions can provide us with insights in past cultural processes and use of landscape. Finally, such an inventory would represent an important decision and planning instrument for future archaeological research projects in the area.

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