# AUTOMATIC DETECTION OF HEDGES AND ORCHARDS USING VERY HIGH SPATIAL RESOLUTION IMAGERY

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**ABSTRACT:**

Automatic mapping and monitoring of agricultural landscapes using remotely sensed imagery has been an important research problem. This paper describes our work on developing automatic methods for the detection of target landscape features in very high spatial resolution images. The target objects of interest consist of hedges that are linear strips of woody vegetation and orchards that are composed of regular plantation of individual trees. We employ spectral, textural, and shape information in a multi-scale framework for automatic detection of these objects. Extensive experiments show that the proposed algorithms provide good localization of the target objects in a wide range of landscapes with very different characteristics.

## 1 INTRODUCTION

Several EU Member States have defined various regulations for the planning, control, maintenance, and monitoring of agricultural sites as part of the EU Common Agricultural Policy. Remote sensing has long been acknowledged as an important tool for the classification of land cover and land use, and provides potentially effective and efficient solutions for the implementation of such regulations. Consequently, development of automatic and robust classification methods has become an important research problem when the analysis goes beyond local sites to cover a wide range of landscapes in national and even international levels.

We have been developing pattern recognition techniques for automatic detection of target landscape features in very high spatial resolution (VHR) images. Classification of land cover has traditionally been performed using pixel-based spectral information given as input to statistical classifiers. However, detection of specific objects is not necessarily accurate when the goal is to classify the whole land cover. Furthermore, it may not be possible to discriminate between certain terrain classes using only spectral information in VHR images with limited spectral resolution. Therefore, it is of great interest to find new methods that incorporate new types of information peculiar to such images.

This paper focuses on the detection of *hedges* that are linear strips of woody vegetation and *orchards* that are composed of regular plantation of individual trees. Hedge detection exploits the spectral, textural, and shape properties of objects using hierarchical feature extraction and decision making steps. Spectral and textural information are used to select groups of pixels that belong to woody vegetation. Shape information is used to separate the target objects from other tree groups and quantify the linearity of these objects. Extensive experiments using QuickBird imagery from three EU Member States show that the proposed algorithms provide good localization of the target objects in a wide range of landscapes with very different characteristics.

Orchard detection uses a structural texture model that is based on the idea that textures are made up of primitives appearing in a near-regular repetitive arrangement. The texture model for the orchards involves individual trees that can appear at different sizes with spatial patterns at gradually changing orientations. The former is related to the granularity of the texture primitives, and the latter corresponds to the structural properties of the texture. The method uses an unsupervised signal analysis framework that can localize regular textured areas along with estimates of granularity and orientations of the texture primitives in complex scenes. Experiments using Ikonos and QuickBird imagery of hazelnut orchards in Northern Turkey show good localization results even when no sharp boundaries exist in the image data.

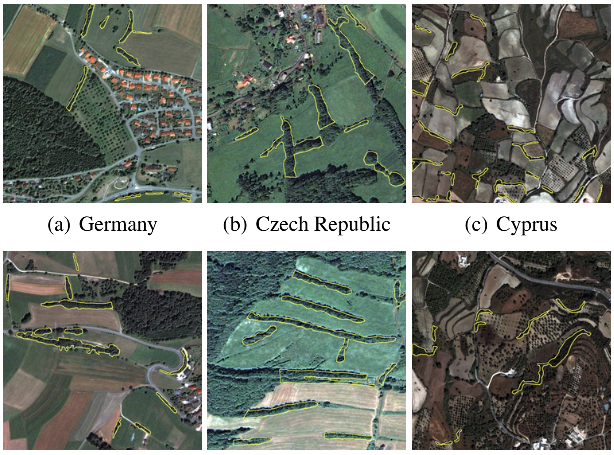
The rest of this paper is organized as follows. Section 2 describes the approach for hedge detection. Section 3 provides an overview of orchard detection. Section 4 concludes the paper. Full description of the proposed methodology, detailed discussion of related work, and detailed performance evaluation can be found in (Aksoy et al., 2010, Yalniz and Aksoy, 2010, Yalniz et al., 2010).

## 2 HEDGE DETECTION

The framework that we developed for hedge detection exploits spectral, textural, and object shape information using hierarchical feature extraction and decision making steps. First, pixel-based spectral and multi-scale textural features are extracted from the input panchromatic and multispectral data. Then, discriminant functions trained on combinations of these features are used to obtain the candidate objects (woody vegetation). Finally, a shape analysis step identifies the linear structures within the candidate areas and separates the target objects of interest from other tree groups. The parts of the candidate objects that satisfy the width and length criteria are labeled as detected targets (hedges). These steps are summarized below. Experiments are also presented using QuickBird imagery from three European sites with different characteristics. More details can be found in (Aksoy et al., 2010).

### 2.1 Study Sites

Panchromatic and pan-sharpened QuickBird-2 sensor data with 60 cm spatial resolution were employed in this study. The data used were from three EU member states with a hedge conservation standard: Baden-Württemberg, Germany; Decin, Czech Republic; and Paphos, Cyprus. These sites were chosen to collect a diverse sample of hedges with different characteristics. The Baden-Württemberg site is a rolling agricultural landscape typical of large parts of the temperate EU, with large clumps of variably sized agricultural parcels intersticed with medium and large forest patches. Hedges are nearly exclusively parcel separations. Pasture dominated Decin site hedges are much larger on average and riparian vegetation is more frequent. Paphos site represents a rather extreme situation of thin hedges in a very fragmented



(a) Germany (b) Czech Republic (c) Cyprus

(d) Germany (e) Czech Republic (f) Cyprus

Figure 1: Example QuickBird images (pan-sharpened visible bands) containing hedges marked with a yellow boundary by an expert. Raster images in this paper are $1000 \times 1000$ pixels in size corresponding to $600 \times 600$ m.

environment containing many other small linear features. Performance evaluation was done using a total of 33 subscenes with 11 subscenes of size $1000 \times 1000$ pixels cut from each site. Examples are shown in Figure 1.

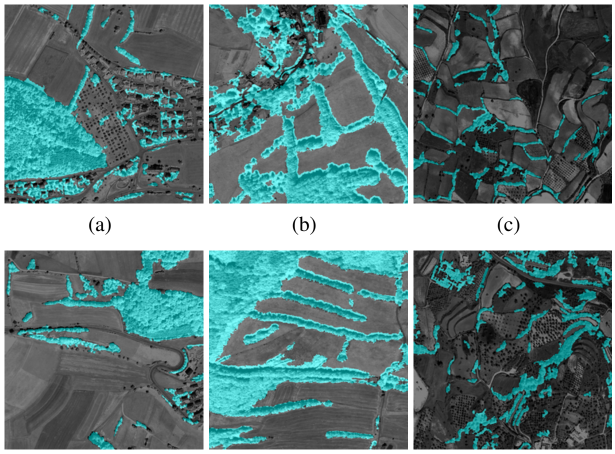
### 2.2 Pre-processing

The first step of the analysis consisted of low-level image processing tasks where pixel-based spectral and multi-scale textural features were extracted from the input panchromatic and multispectral data. The normalized difference vegetation index (NDVI) was computed from the pan-sharpened multispectral data to separate green vegetation from the rest of the land cover. Texture features were used for identifying areas that have similar spectral responses but different spatial structures. In particular, Gabor features and granulometry features were used to model the arrangements of individual trees and the appearance of linear structures with respect to their surroundings. Gabor features were extracted by applying a bank of scale and orientation selective filters to the panchromatic band. Six scales were designed to include both the fine texture of individual trees within a hedge and the coarse texture of hedges among agricultural fields. Granulometry features were extracted using morphological opening and closing of the panchromatic image with a family of structuring elements with increasing sizes. These features were used to summarize the size distribution of image structures brighter or darker than their neighborhood.

### 2.3 Identification of Candidate Objects

The next step was to find the image areas that gave high responses to the extracted features so that they could be considered as candidate objects. We used a two-step decision process. First, a threshold on NDVI was used to separate green vegetation from the rest of the land cover. The threshold was selected so that there was no omission of any hedge structure. However, we observed that such thresholding could not distinguish hedges from other types of vegetation and kept many fields, large groups of trees and other vegetated areas in the output. On the other hand, the thresholding eliminated some linear human-made structures that gave high responses to the texture features.

Given the obtained vegetation mask, the next step was to identify candidate objects according to their texture characteristics.



(a) (b) (c)

(d) (e) (f)

Figure 2: Example results for woody vs. non-woody vegetation classification. The image areas identified as woody vegetation are marked as green on the panchromatic image. Note that woody vegetation can have very different appearances in different sites.

Pixel-based texture modeling was not sufficient for detecting the linearity of a structure but was capable of modeling its woodiness. Hence, we concentrated on the separation of woody vegetation from the rest of the areas in the vegetation mask. Manual labeling of image areas as woody vs. non-woody vegetation was used to generate the ground truth for training and evaluation. Different combinations of features and different classifiers were studied. The Gaussian maximum likelihood classifier was found to perform as good as any other classifier with an overall classification accuracy of 94.83%, and was used in the rest of the analysis.

After the discriminant function identified the pixels that could belong to targets of interest (woody vegetation), connected sets of these pixels were grouped to obtain the candidate objects. Example results are shown in Figure 2.

### 2.4 Detection of Target Objects

After the candidate objects were found, object shape information was used so that the objects could be labeled as target or are rejected. An important observation was that the results of the pixel grouping in the previous step were not directly suitable for computing object level features. The reasons were twofold: hedges were often connected to other larger groups of trees, and they often followed natural boundaries where they did not necessarily exhibit a perfectly straight structure. Hence, an important step was the separation of hedges from other tree groups and piecewise linearization of the object regions where linearity was defined as piecewise elongation along the major axis while having an approximately constant width, not necessarily in the strict sense of a perfectly straight line.

The object-based feature extraction process used morphological top-hat filtering to locate the woody vegetation areas that fell within the width limits of an acceptable hedge and skeletonization and an iterative least-squares fitting procedure to quantify the linearity of the objects. Given two thresholds that specified the maximum and minimum acceptable width of a hedge, the morphological filtering step eliminated the structures that were too wide or too narrow. This also decreased the computation time by excluding the structures that were not within the shape limits of an acceptable hedge from further processing. However, it did not guarantee that the remaining structures were linear.

The next step used skeletonization as a structural representation of the object shapes, and an iterative least-squares fitting based

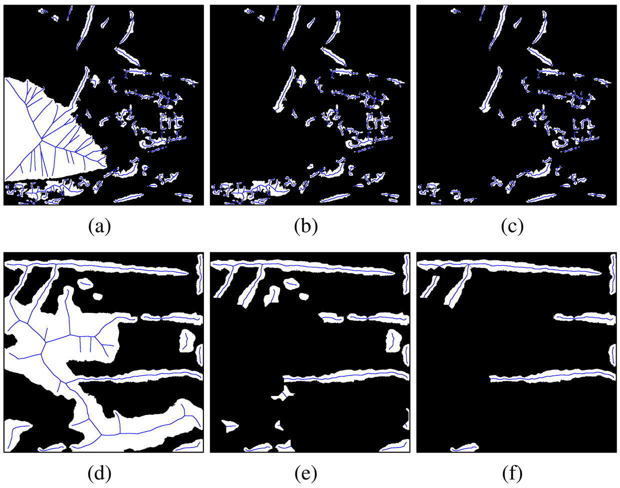


Figure 3: Example results for object-based feature extraction. The first column shows initial skeletons overlayed on the woody classification maps. The second column shows the parts that remained after morphological top-hat filtering. The third column shows the objects corresponding to the final set of segments selected as linear using the least-squares fitting procedure.

segment selection procedure was employed to extract the parts of this representation that might correspond to a hedge. First, the skeleton of the binary classification map of candidate objects was computed as an approximation of the symmetry axis of the objects. The output of this step was the set of points on the skeleton, and, for each point an estimate of the radius (width) of the shape around that point. We assumed that the linearity of a segment could be modeled by the uniformity of the radii along the skeleton points that corresponded to the uniformity of the width perpendicular to the symmetry axis. This assumption was implemented using an iterative least-squares procedure for selecting the group of pixels having uniform radii. The measure of how well a set of points were uniform in radii was computed using the least-squares error criterion, and the subsegments passing this criterion were kept as candidates for the final decision. This idea is similar to a least-squares procedure of fitting a line to pixel locations along a uniform slope, but the main difference is that the fitting is done to the radii values instead of the position values because the hedges that follow natural paths do not necessarily exhibit straight structures in terms of positions along a fixed slope but can be discriminated according to the uniformity of their width along a symmetry axis. Examples are shown in Figure 3.

The final set of shape features consisted of the aspect (length/width) ratio for each resulting object. The length was calculated as the number of points on the skeleton of the corresponding subsegment, and the width was calculated as the average diameter for the points on the skeleton of the subsegment. The final decision for accepting a segment as a target object was done using a threshold on aspect ratio.

### 2.5 Performance Evaluation

Manual photo-interpretation was used to produce the reference data. Object-based performance evaluation was done in terms of the overlaps between the skeletons of the reference objects and the detected objects. The objects whose skeletons had an overlap of at least 60% were considered as matches. Object-based precision (the number of true positives divided by the total number of objects labeled as hedges by the algorithm) and recall (the number of true positives divided by the total number of objects labeled as hedges by the expert) were used as the quantitative performance criteria. Overall precision was 35.23% and recall was

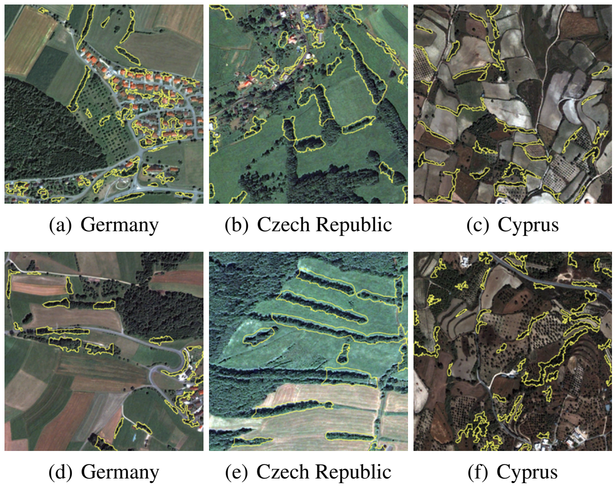


Figure 4: Example results for hedge detection. The objects detected as hedges are marked with a yellow boundary.

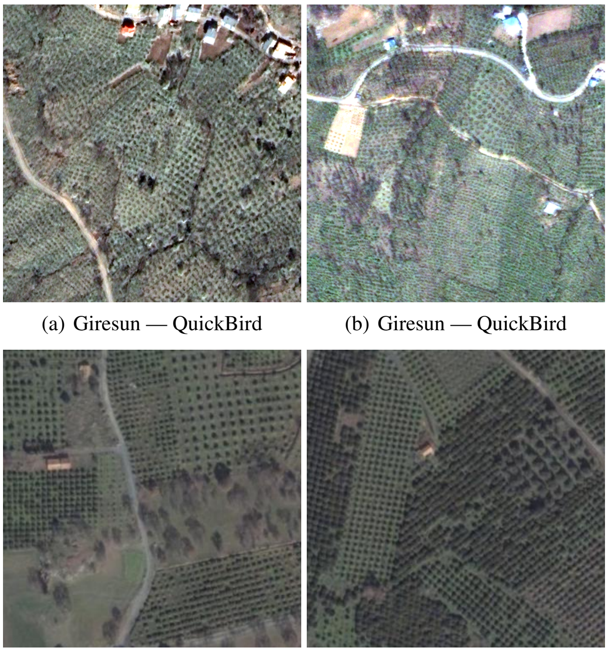
58.69%. Example results are shown in Figure 4. Visual interpretation showed that the performance was actually better than the quantitative results due to limitations in the reference data. False negatives were mainly caused by the errors during the identification of candidate objects. False positives were mainly caused by groups of individual but nearby trees in orchards, groups of trees in residential areas, and linear vegetation that did not look woody enough and was not included in the reference data.

## 3 ORCHARD DETECTION

Our framework for orchard detection is based on texture analysis of panchromatic data. The approach starts with a pre-processing step involving multi-granularity isotropic filters for enhancing tree-like objects in the image. The local maxima in the filter responses are assumed to correspond to potential tree locations, and the regularity of these locations along a scan line with a particular orientation in the image is measured using periodicity analysis of projection profiles within oriented sliding windows. The periodicity analysis is performed at multiple orientations and granularities to compute a regularity score at each pixel. Finally, a regularity index is computed for each pixel as the maximum regularity score and the principal orientation and granularity for which this score is maximized. The image areas that contain an orchard composed of regular arrangements of trees can be localized by thresholding this regularity index. These steps are summarized below. Experiments are also presented using Ikonos and QuickBird imagery of a site in Turkey containing hazelnut orchards. More details can be found in (Yalniz and Aksoy, 2010, Yalniz et al., 2010).

### 3.1 Study Sites

Panchromatic Ikonos and QuickBird-2 sensor data were employed in this study. The area experimented corresponded to the Merkez county in the province of Giresun in the Black Sea region of Turkey. A specific property of the region is the strong relief, which makes hazelnut production the main cultivation there. In addition, the hazelnut orchards in the region are often small and have a high planting density relative to orchards in other countries. Performance evaluation was done using a total of 15 subscenes with five subscenes of size $1000 \times 1000$ pixels cut from each of one Ikonos and two QuickBird images. Seven images, each with size $1680 \times 1031$ pixels, that were saved from Google Earth over Izmir, Turkey were also used in the experiments. Examples are shown in Figure 5.



(a) Giresun — QuickBird (b) Giresun — QuickBird

(c) Izmir — Google Earth (d) Izmir — Google Earth

Figure 5: Example images containing orchards. Color data are shown but only the panchromatic information was used in the study.

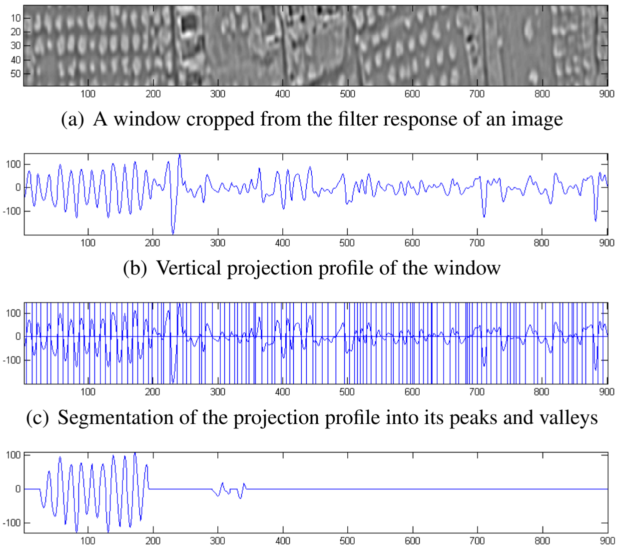
### 3.2 Pre-processing

The tree model was assumed to correspond to a filter for which the image areas with a high response were more likely to contain trees than areas with a low response without any strict requirement for exact detections. We used the Laplacian of Gaussian filter as a spot filter for a generic tree model sensitive to contrast differences in any orientation. The isotropic spot filter had a single scale parameter corresponding to the Gaussian function, and this parameter could be selected according to the sizes (granularities) of the trees of interest. Note that any other filter could also be used because the following step will use the filter responses that enhance the tree-like objects in the image.

### 3.3 Regularity Detection

After the tree-like objects were enhanced in an image, the pixels having high responses (local maxima) on a scan line along the image indicated possible locations of such objects. In a neighborhood with a regular repetitive structure, the locations of local maxima along the scan line with an orientation that matched the dominant direction of this structure also had a regular repetitive pattern. The next step involved converting the image data into 1D signals using projection profiles at particular orientations, and quantifying the regularity of the trees along these orientations in terms of periodicity analysis of these profiles.

Given a scan line representing a particular orientation, the vertical projection profile was computed as the summation of the values in individual columns (in perpendicular direction to the scan line) of an oriented image window constructed symmetrically on both sides of this scan line. This profile would contain successive peaks with similar shapes if the orientation of the scan line matched the orientation of the texture pattern. The regularity of the texture along a particular orientation was assumed to be represented in the periodicity of the corresponding projection profile. Since it might not always be possible to find a perfect period, especially for natural textures, we designed an algorithm



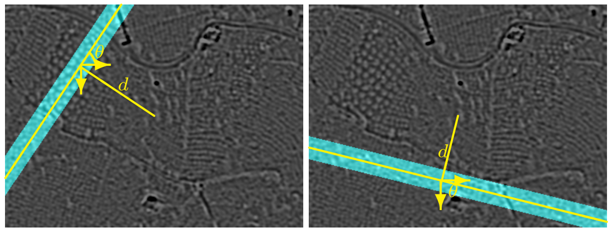

(a) A window cropped from the filter response of an image

(b) Vertical projection profile of the window

(c) Segmentation of the projection profile into its peaks and valleys

(d) Periodic intervals located in the profile signal

Figure 6: Periodicity analysis of the projection profile of an image window.



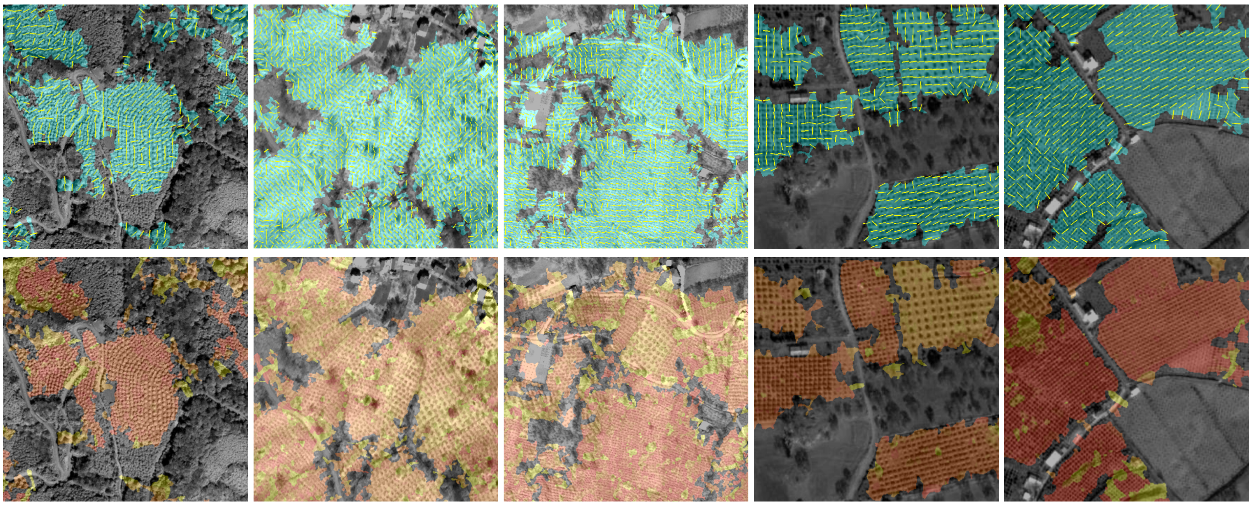

(a) $d = -120, \theta = -55°, \delta = 30$ (b) $d = 90, \theta = 15°, \delta = 30$

Figure 7: Example windows for computing the projection profiles. Each window is marked as green together with the scan line that passes through its symmetry axis that is marked as yellow.

that measured the amount of periodicity and located the periodic part within the larger profile signal. This was achieved using three constraints. The first constraint used the peaks and valleys of the profile signal where the peaks were assumed to correspond to the trees and the valleys represented the distance between consecutive trees. A regularity score between 0 and 1 was computed for each pixel using signal analysis so that pixels with a score close to 1 were candidates to be part of a regular periodic signal. The second constraint selected the parts of the signal where there were alternating peaks and valleys corresponding to a regular planting pattern of trees and the spacing between the trees. Finally, the third constraint checked the width of each peak and eliminated the ones that were too narrow or too wide with respect to the sizes of the trees of interest. Figure 6 shows an example for periodicity analysis.

### 3.4 Multi-orientation and Multi-granularity Analysis

An image may contain periodic textures at multiple orientations composed of multiple granularities of texture primitives. Therefore, different granularities were approximated using different spot filters, and the projection profiles for different orientations were analyzed by sliding image-wide oriented windows over each spot filter output. Example windows are shown in Figure 7. The windows were parametrized by a distance parameter $d$, an orientation parameter $\theta$, and a height parameter $\delta$ with respect to the center pixel of the image as the origin. The resulting regularity scores for all orientations and all granularities for all pixels were stored in a four dimensional matrix denoted as $\rho(r, c; \theta, g)$ where



(a) Giresun — Ikonos (b) Giresun — QuickBird (c) Giresun — QuickBird (d) Izmir — Google Earth (e) Izmir — Google Earth

Figure 8: Example results for orchard detection. The areas detected by thresholding the regularity index are marked as green on the panchromatic image, along with orientation estimates marked as yellow line segments (top row) and scale estimates marked using shades of red and yellow (bottom row).

$(r, c)$ were the pixel locations, $\theta \in [-90^\circ, 90^\circ)$ were the orientations, and $g$ represented the granularities.

### 3.5 Texture Segmentation

The goal of the last step was to compute a regularity index for each pixel to quantify the structure of the texture in the neighborhood of that pixel along with estimates of the orientation of the regularity as well as its granularity. For robustness, it was expected that the regularity values were consistent among neighboring pixels for a certain range of orientations and granularities. The noisy cases were suppressed by convolving $\rho(r, c; \theta, g)$ with a four dimensional Gaussian filter with size $11 \times 11 \times 11 \times 3$. A final regularity index was defined as the maximum regularity score at each pixel and the principal orientation and granularity for which this score was maximized. Texture segmentation was performed by thresholding this regularity index.

### 3.6 Performance Evaluation

The performance of orchard detection was also evaluated using reference data produced using manual photo-interpretation. Pixel-based precision and recall were used as the quantitative performance criteria. Overall precision for Giresun data was obtained as 47.07% and recall was obtained as 78.11%. When the performances on Ikonos data and QuickBird data were compared, higher accuracy was observed for the QuickBird data due to the increased spatial resolution. We also observed that the time of the image capture affected the results as higher accuracy was obtained when the individual trees were more apparent in the panchromatic image. Overall precision for the Izmir data taken from Google Earth was obtained as 85.46% and recall was obtained as 88.35%. The lower accuracy for the Giresun data was mainly due to the irregularities in the planting patterns, mixed appearances of other trees within the orchards, and the deformations in the visual appearance of the patterns due to the strong relief in the region. Example results for local details of orchard detection along with orientation and granularity estimates are shown in Figure 8. Most of the false positives were observed along roads where there was a repetitive contrast difference on both sides, and around some building groups where a similar regular contrast difference was observed due to neighboring edges. False negatives mostly occurred at small vegetation patches that were marked in the reference data due to a few rows of regularly planted trees but were not large enough for the algorithm.

## 4 CONCLUSIONS

We presented new methods for automatic detection of hedges that are defined as linear strips of woody vegetation and orchards that are composed of regular plantation of individual trees as target objects in VHR images. The approach for hedge detection exploited the spectral, textural, and shape properties of objects using hierarchical feature extraction and decision making steps. Orchard detection used a structural texture model that was based on the idea that textures were made up of primitives (trees) appearing in a near-regular repetitive arrangement (plantation patterns). An important design goal was to minimize the amount of supervision needed so that the methods could be applied on a wide range of landscapes with very different characteristics. Experiments using Ikonos and QuickBird imagery showed good detection and localization results on a diverse set of test sites.

## ACKNOWLEDGMENT

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