Learning to automatically detect avalanche deposition from SAR satellite imagery

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Detect avalanche deposition (debris) for:
* identifying avalanche risk zones/periods
* improving physical models of prediction
* studying the variability on long-term scale

Recent studies [1,2] showed the potential of using Sentinel-1 SAR data, but no external ground truth was used to validate.

Can we learn avalanche deposition from SAR with an independent event inventory?

DATA

Sentinel-1 satellites SAR (synthetic aperture radar):
- Sensitive to snow properties [1]
- Penetrate through clouds
- 20m resolution, every 6 days

Season 2017-18:
- Backscatter coefficients VV & VH
- maps of orientation, altitude, slope

Validation:
- avalanche event site inventories
- 4000 avalanche corridors

METHODS

1. Starting route with potential source areas (avalanche inventory)

SAR use (ESA) + DEM (National Institute for Geographic and Forestry Information)

Calibration, pairwise registration and geo-localisation

Features masked with distorted areas

Features
- VV as 10log10(VV/VVsum)
- VV (previous pass)
- VH as 10log10(VH/VHsum)
- VH (previous pass)
- VV signal
- VH signal
- Orientation
- Slope
- Satellite angle

Classification approaches (with param. grid search):
- Nearest Neighbors
- Linear SVM
- Decision Tree
- Random Forest
- Neural Net (MLP)
- AdaBoost

RESULTS

Baseline method [1]:

<table>
<thead>
<tr>
<th>Method/Features (Accuracy score in %)</th>
<th>VV</th>
<th>VV + VH</th>
<th>VV + VH + other features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nearest Neighbors Valid. set</td>
<td>64.3</td>
<td>66.7</td>
<td>72</td>
</tr>
<tr>
<td>Linear SVM Valid. set Valid. set</td>
<td>65.5</td>
<td>65.5</td>
<td>69.8</td>
</tr>
<tr>
<td>Decision Tree Valid. set</td>
<td>67.3</td>
<td>69.4</td>
<td>72.7</td>
</tr>
<tr>
<td>Random Forest Test set</td>
<td>67.4</td>
<td>70</td>
<td>75</td>
</tr>
<tr>
<td>Neural Net (MLP) Test set</td>
<td>67</td>
<td>69</td>
<td>73.3</td>
</tr>
<tr>
<td>AdaBoost</td>
<td>67.4</td>
<td>69</td>
<td>73.3</td>
</tr>
</tbody>
</table>

* if the threshold was not reached previously (6 days before)

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Idea for future work. Use convolutional neural networks for classification from image patches as input (include the context)

References: