Automatic crater detection based on random forests, existing crater map, and spatial structural information from DEM

Cheng-Zhi QIN

(State Key Laboratory of Resources and Environment Information System, Institute of Geographic Sciences & Natural Resources Research, Chinese Academy of Sciences)

2019-4-5
1. Background & study issue
2. Basic idea
3. Design of the proposed approach
4. Case study
5. Evaluation results & discussion
6. Summary
1. Background

Impact crater map is important for

- Research on evolution of stars’ surfaces (Neukum et al., 2001)
- Engineering such as probe landing and self-driving

(Neukum et al., 2001; Cheng et al., 2016)
Crater detection

- Traditional way: manual delineation based on visual judgement

**Shortcomings**: labor-intensive, low efficiency, and high cost
Crater detection approaches (CDAs) based on image analysis

- Image characteristics of craters:
  1) Ring-like rim of crater
  2) Pattern of Bright-dark

(Sawabe et al., 2006; Urbach & Stepinski, 2009; Ding et al., 2011)

(Barata et al., 2004; Kim et al., 2005; Salamunićcar & Lončarić, 2008; Salamunićcar et al., 2010; Luo et al., 2011)

Shortcomings:
- Image quality issue due to lighting conditions, terrain conditions, etc. (Stepinski et al., 2009)
- 2D image cannot well reflect the spatial structure of craters, especially of those superimposed craters and degraded craters.
CDAs based on terrain analysis

- Gridded DEM records 3D information of craters and thus could reveal the spatial structure of craters (Stepinski et al., 2009; Wan et al., 2012)

- General workflow: two-stage process
  (Bue & Stepinski, 2007; Stepinski et al., 2009; Stepinski et al., 2012; Wan et al., 2012; Yue et al., 2013; Zuo et al., 2015; Vamshi et al., 2016; Liu et al., 2017)

![Diagram of two-stage process](image)

- **Stage 1**: detect crater candidate area at cell level
- **Stage 2**: determine craters at object level
Existing CDAs based on terrain analysis

- **Type 1: Depression-filling & manually-determined rules on shape** (Bue & Stepinski, 2007; Wan et al., 2012; Yue et al., 2013; Zuo et al., 2015; Vamshi et al., 2016; Liu et al., 2017)
  - **Shortcomings:** View craters as simple round depressions, thus ignore the spatial structural information of craters; limit effectiveness

```
<table>
<thead>
<tr>
<th>DEM</th>
<th>flooding</th>
<th>Crater candidate area</th>
<th>Judge the roundness of crater candidate objects</th>
<th>Crater map</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Stage 1</td>
<td>Stage 2</td>
</tr>
</tbody>
</table>
```

- **Type 2: AutoCrat** (Stepinski et al., 2009; Stepinski et al., 2012)
  - **Shortcomings:** Using a set of simple shape indices only partly consider the spatial structural information of craters (not inside craters)

```
<table>
<thead>
<tr>
<th>DEM</th>
<th>Depression-finding: Slope gradient change + connected component anal.</th>
<th>Crater candidate area</th>
<th>C4.5 decision tree with shape indices of crater objects: diameter; depth; depth-diameter ratio, elongation, lumpiness</th>
<th>Crater map</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Stage 1</td>
<td>Stage 2</td>
</tr>
</tbody>
</table>
```
Study issue

- Existing CDAs mainly consider conceptual crater (with simplified shape/spatial structure).
- Spatial structure of real craters is complicated

How to design a new automatic approach to detecting craters based on DEM

- effectively consider the spatial structural information of real craters
2. Basic idea

- Mining implicit expert knowledge on spatial structure of real craters;
- and using it to detect craters in other areas with DEM

A new automatic approach to detecting craters
Framework of the proposed approach

1. Collect training samples at cell level
   - Training area
     - DEM
     - Crater map
   - Collect training samples at object level
2. Prepare input features with spatial structural info (cell level)
3. Machine learning classifier 1 (cell level)
4. Stage 1
5. Stage 2
6. Collect training samples at object level
7. Prepare input features with spatial structural info (object level)
8. Machine learning classifier 2 (object level)
9. Application area
   - DEM
10. Crater detection results
3. Detailed design of the proposed approach

- Machine learning classifier: Random Forests (Breiman, 2001)

(Bassa et al., 2016)
How to train RF classifier to detect crater candidate cells?

1. Collect training samples at cell level
2. Prepare input features with spatial structural info (cell level)
3. Random Forests classifier 1 (cell level)
4. Crater candidate cells
5. Stage 1
6. Training
7. Applying
8. Stage 2
9. Collect training samples at object level
10. Prepare input features with spatial structural info (object level)
11. Random Forests classifier 2 (object level)
12. Crater candidate objects
13. Application area
14. DEM
15. Crater detection results
Input features with spatial structural information at cell level

A location with different analysis scale could show different landform element types (Fisher et al., 2004; Deng et al., 2008)

- **Multi-scale landform element** (Kang et al., 2016)
  - Extend the Geomorphons method (Jasiewicz & Stepinski, 2013), which derives landform element at single analysis scale, to multi-scale
  - Determine feature point at each analysis scale based on Douglas & Peucker (1973)

Openness (Yokoyama et al., 2002)

Determine feature point with max beta-angle (Jasiewicz & Stepinski, 2013)

End point: anal scale[1..N]
Training samples with input features for RF at cell level

- Positive sample

- Negative sample

• Input feature: multi-scale landform elements for each sample (i.e., landform element types at a series of analysis scale)
How to create crater candidate objects from candidate cells?

1. **Stage 1**
   - Collect training samples at object level
   - Prepare input features with spatial structural info (object level)
   - Random Forests classifier 2 (object level)
   - Crater candidate objects
   - Training
   - Applying

2. **Stage 2**
   - Random Forests classifier 1 (cell level)
   - Crater candidate cells
   - Features of cell: Multi-scale landform element
   - Collect training samples at object level

**Training area**
- Crater map
- DEM

**Application area**
- DEM

**Crater detection results**
- Training samples: crater cells & non-crater cells
crater candidate cells $\rightarrow$ candidate objects

- De-noising by mathematical morphology (open op.) + DBSCAN clustering
- Random Forests classifier 1 (cell level)
- Minimum circumscribed circle $\rightarrow$ candidate object

Crater candidate cells

Crater candidate objects
How to train RF classifier to determine craters?

**Stage 1**
- Training samples: crater cells & non-crater cells
- Features of cell: Multi-scale landform element
- Random Forests classifier 1 (cell level)
- Crater candidate cells

**Stage 2**
- Collect training samples at object level
- Prepare input features with spatial structural info (object level)
- Random Forests classifier 2 (object level)
- Crater candidate objects
- Crater detection results

**Application area**
- DEM
Input features with spatial structural information at object level

Crater map + DEM

Spatial structure of real craters

Radial elevation profile

Normalized Relief

Radial profile

Input feature
(with same dimension for every sample for a RF)

Radius of candidate object
Train the object-level RF classifier to determine craters

- Train the object-level RF with those training samples with features (normalized radial elevation profile) in training area

- Positive sample

- Negative sample

- The trained RF classifier → Judge the candidate objects in application area

A candidate object will be recognized as real crater, if the ratio of its radial profiles being of crater > a threshold (e.g., 50%).
Detailed workflow of the proposed approach

Training samples:
- crater cells & non-crater cells

Features of cell:
- Multi-scale landform element

Random Forests classifier 1
- (cell level)
- Crater candidate cells

Training area
- Crater map
- DEM

Application area
- DEM

Crater candidate objects

Features (obj. level):
- normalized radial elevation profile

Random Forests classifier 2
- (object level)
- Crater detection results

Stage 1
- Training
- Applying

Stage 2
- Training
- Applying

Training samples:
- crater & non-crater radial profiles
4. Case study: lunar impact craters

Data source:

• LOLA (Lunar Orbiter Laser Altimeter) crater map (diameter of crater ≥ 20 km) (Kadish et al., 2011)
• Chang’E-1 DEM (resolution: 500 m) (Wu et al., 2011)
Study area settings

- Training area: 78,000 km$^2$; 490*640 cells
- Application area: 476,000 km$^2$; 1190*1600 cells (~6 times of training area)
  - Distance: ~2000 km
Evaluation method

- The reference approach: the state-of-the-art AutoCrat (Stepinski et al., 2009; Stepinski et al., 2012)

- Quantitative evaluation
  1) Individual correctness index (C-value)
     \[
     C\text{-value} = \frac{\text{IntersectionArea}(T, D)}{\text{UnionArea}(T, D)}
     \]
     (T: the crater in LOLA; D: the crater recognized by the proposed approach)

     ✓ A crater is detected “correctly”, if the C-value > a user-assigned C-threshold
     (0.3, 0.4, 0.5, 0.6, and 0.7 were tested in this study)

  2) Matching ratio = \frac{\text{Count(craters detected correctly)}}{\text{Count(LOLA craters)}} \times 100%
4. Evaluation results & discussion

- Crater count in application area

**LOLA: 92; the proposed approach: 94; AutoCrat: 71**
“Correctly” detected craters with different individual correctness threshold

<table>
<thead>
<tr>
<th>C-threshold</th>
<th>Craters matching to LOLA</th>
<th>matching ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>the proposed appr.</td>
<td>AutoCrat</td>
</tr>
<tr>
<td>0.7</td>
<td>43</td>
<td>37</td>
</tr>
<tr>
<td>0.6</td>
<td>56</td>
<td>44</td>
</tr>
<tr>
<td>0.5</td>
<td>62</td>
<td>49</td>
</tr>
<tr>
<td>0.4</td>
<td>68</td>
<td>49</td>
</tr>
<tr>
<td>0.3</td>
<td>71</td>
<td>51</td>
</tr>
</tbody>
</table>

(C-value >= 0.5)

<table>
<thead>
<tr>
<th>craters matching to LOLA</th>
<th>the proposed appr.</th>
<th>AutoCrat</th>
</tr>
</thead>
<tbody>
<tr>
<td>craters correctly detected by both appr.</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td>craters correctly detected just by one appr.</td>
<td>22</td>
<td>9</td>
</tr>
<tr>
<td>Matching ratio</td>
<td>67.4%</td>
<td>53.3%</td>
</tr>
</tbody>
</table>
Discussion

Different types of craters detected correctly by the proposed approach

- Simple craters / degraded craters
- Superimposed craters
- Multiple connected craters created probably by one impact event
Discussion

• Frequency of detected craters with different radiiueses

The proposed approach showed reasonable extrapolation performance.
6. Summary

- **An automatic approach to detecting impact crater**: Machine learning + existing crater map + spatial structural information from DEM
  - mine implicit expert knowledge on spatial structure of real craters from existing crater map
  - effectively consider the spatial structural information inside real craters
    - from two levels, respectively (i.e., cell, and object)

- **Potential**
  - The methodology and framework of the proposed approach could also be applied to mapping other geomorphologic types (e.g., volcanic crater, sand dune, V-shape channel, …).
Thank You for Your Attention!

Acknowledgements: grant from Chinese Academy of Sciences (Project No.: XDPB11)

Email: qincz@lreis.ac.cn
Webpage: http://people.ucas.ac.cn/~qincz?language=en