PROJECT SIDEWALK: MAPPING THE ACCESSIBILITY OF THE WORLD THROUGH GOOGLE STREET VIEW

@jonfroehlich | Associate Professor | Computer Science | University of Washington
Our Mission

Design, build, & study interactive tools & techniques to address pressing societal challenges
MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION
Makeability Lab

Four Focus Areas

Environmental Sustainability
Health & Wellness
Accessibility
STEM Education
MAKEABILITY LAB
FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION
ENVIRONMENTAL SUSTAINABILITY

PERVASIVE THERMOGRAPHY

With recently graduated UMD CS PhD Student Matt Mauriello, now a post-doc at Stanford

[UbiComp’14, CHI’15 Honorable Mention, HBI’16, CHI’17, UbiComp’17 DC, MobileHCI’18]
FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION
HEALTH & WELLNESS

DESIGNING HEALTH SUPPORT SYSTEMS

[CHI’13 Best Paper, CHI’14]
MAKEABILITY LAB
FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION
MAKEABILITY LAB
FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION
MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

HEALTH & WELLNESS

ACCESSIBILITY

STEM EDUCATION
How can we...

develop solutions that collect, model, verify, & visualize urban accessibility at scale?

PROJECT SIDEWALK
[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13 Best Paper, UIST'14, TACCESS'15, SIGACCESS'15, CHI'16, ASSETS'17, ASSETS'18 x2]
30.6 million U.S. adults have a mobility impairment

Source: US Census, 210
15.2 million use an assistive aid

Source: US Census, 210
PHYSICAL OBSTACLES
INCOMPLETE SIDEWALKS
Accessible infrastructure has a significant impact on the independence and mobility of citizens

[Thapar et al., 2004; Nuernberger, 2008]
I usually don’t go where I don’t know [about accessible routes]

-P3, congenital polyneuropathy
The National Council on Disability noted that there is no comprehensive information on “the degree to which sidewalks are accessible” in cities.

National Council on Disability, 2007
The impact of the Americans with Disabilities Act: Assessing the progress toward achieving the goals of the ADA
There are many approaches for data collection but they typically require **onsite reporting**, which **limits scalability**.
ACCESSIBILITY DATA COLLECTION

TRADITIONAL ACCESSIBILITY AUDITS

Walkability Audit
Wake County, North Carolina

Walkability Audit
Wake County, North Carolina

Safe Routes to School Walkability Audit
Rock Hill, South Carolina
ACCESSIBILITY DATA COLLECTION

MOBILE REPORTING SOLUTIONS

http://www1.nyc.gov/311/index.page
ACCESSIBILITY DATA COLLECTION

MOBILE REPORTING SOLUTIONS

The NYC311 app has a specific option for broken sidewalks.
Get Involved while on-the-go.

Report, track, and discuss issues in your neighborhood. With just a few clicks, fellow citizens and your government can find and manage 311 issues instantly. Available across devices and on mobile web browsers, anyone can get involved in their community.

Download Now!

Be a good neighbor. Everywhere.
ACCESSIBILITY DATA COLLECTION

REPORTING ON ACCESSIBILITY OF PLACES

http://wheelmap.org

http://axsmap.com

http://accesstogether.org
ACCESSIBILITY DATA COLLECTION

REPORTING ON ACCESSIBILITY OF PLACES

Important crowdsourcing tools

Reliance on local population for reporting limits who can supply data and how much they supply

Recent survey by Ding et al., 2014 found that only 1.6% of Wheelmap POIs had data about accessibility

Focus is on places rather than sidewalk infrastructure
We are pursuing a complementary two-fold approach
To develop scalable methods that mine massive repositories of online map imagery to identify accessibility problems semi-automatically.
To enable new urban accessibility analyses and create accessibility-aware mapping tools not previously possible.
Mapping the Accessibility of the World

Two Focus Areas

1. Scalable Data Collection Methods

[ASSETS’12, CHI’13, HCOMP’13, ASSETS’13, UIST’14, TACCESS’15, ASSETS’17, ASSETS’18]

2. New Urban Access Analytics & Tools

[SIGACCESS ’15, CHI’16, ASSETS’18]
Is online map imagery a good source for accessibility data?

Can we create interactive tools that enable crowd workers to find accessibility problems?

How can we leverage computational techniques to scale our approach?

[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13, UIST'14, TACCESS'15, ASSETS'17, ASSETS'18]
Is **online map imagery** a good source for accessibility data?

Can we **create interactive tools** that enable crowd workers to find accessibility problems?

How can we **leverage computational techniques** to scale our approach?

1. **SCALABLE DATA COLLECTION METHODS**

[ASSETS’12, CHI’13, HCMP’13, ASSETS’13, UIST’14, TACCESS’15, ASSETS’17, ASSETS’18]
How well do accessibility problems found in Google Street View correspond with the real world?
Can you tell which image comes from Google Street View and which image we took ourselves with our iPhone?
IS GOOGLE STREET VIEW A REASONABLE DATASET FOR ACCESSIBILITY AUDITS?

PHYSICAL AUDITS VS. GSV: SURVEYED 76KM

179 BUS STOPS
Washington DC & Seattle | 42 km surveyed

273 INTERSECTIONS
Washington DC & Baltimore | 34 km surveyed
IS GOOGLE STREET VIEW A REASONABLE DATASET FOR ACCESSIBILITY AUDITS?

COMPARISON RESULTS: SPEARMAN RANK COEFFICIENTS

**BUS STOPS**
- Physical Audit Data
- GSV Audit Data

**INTERSECTIONS**
- Physical Audit Data
- GSV Audit Data

\[ \rho = 0.88 \quad \rho = 0.98 \]

All results statistically significant at \( p < 0.001 \)
Assessing the Built Environment Using Omnidirectional Imagery

Jeffrey L. Wilson, PhD, Chong M. Knafo, PhD, Mario Schectman, PhD, Elizabeth A. Bader, PhD, Arvinder Banerjee, PhD, Morgan Cramm, MPH, Douglas K. Miller, MD

Introduction

Prior studies suggest that the built environment influences physical activity through omnidirectional imagery. However, it is unclear how the built environment influences physical activity through omnidirectional imagery. To address this gap, this study examined the relationship between omnidirectional imagery and physical activity using a novel method of measuring the built environment. The results of this study suggest that omnidirectional imagery is a useful tool for assessing the relationship between the built environment and physical activity.

Methods

The study included a convenience sample of 100 adults who completed a survey and omnidirectional imagery of their neighborhood. Omnidirectional imagery was collected using a 360-degree camera and geographic information system (GIS) software. The built environment was assessed using a standardized questionnaire and GIS data. The omnidirectional imagery was analyzed using image analysis software to determine the number of people engaging in physical activity.

Results

The results of the study suggest that omnidirectional imagery is a useful tool for assessing the relationship between the built environment and physical activity. The omnidirectional imagery showed that people were engaging in physical activity in a variety of locations, including parks, walking paths, and bike paths. The results also showed that the number of people engaging in physical activity was related to the density of the built environment.

Conclusion

Omnidirectional imagery is a useful tool for assessing the relationship between the built environment and physical activity. Further research is needed to determine if omnidirectional imagery can be used to assess the relationship between the built environment and other health-related outcomes.
IS GOOGLE STREET VIEW A REASONABLE DATASET FOR ACCESSIBILITY AUDITS?

CITY INFRASTRUCTURE CHANGES SLOWLY

AVG IMAGE AGE IN BUS STOP DATASET

1.7 yrs (SD=0.7)

AVG IMAGE AGE IN INTERSECTION DATASET

1.5 yrs (SD=0.7)
Official DC.gov dataset for curb ramps hasn’t been updated since 2010.
Google Street View is a reasonable proxy for studying the state of street-level accessibility.
Is online map imagery a good source for accessibility data?

Can we create interactive tools that enable crowd workers to find accessibility problems?

How can we leverage computational techniques to scale our approach?
Is online map imagery a good source for accessibility data?

Can we create interactive tools that enable crowd workers to find accessibility problems?

How can we leverage computational techniques to scale our approach?

SCALABLE DATA COLLECTION METHODS

[ASSETS’12, CHI’13, HCMP’13, ASSETS’13, UIST’14, TACCESS’15, ASSETS’17, ASSETS’18]
CROWDSOURCING ACCESSIBILITY AUDITS

INITIAL CROWDSOURCING SYSTEM

LABELING INTERFACE

VERIFICATION INTERFACE

[ASSETS’12 Poster, CHI’13]
4-STEP PROCESS

1. Find & label problem
1. Find & label problem
CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED LABELING INTERFACE

4-STEP PROCESS
1. Find & label problem
2. Categorize problem
4-STEP PROCESS
1. Find & label problem
2. Categorize problem
4-STEP PROCESS
1. Find & label problem
2. Categorize problem
3. Rate problem severity
CROWDSOURCING ACCESSIBILITY AUDITS
WEB-BASED LABELING INTERFACE

4-STEP PROCESS
1. Find & label problem
2. Categorize problem
3. Rate problem severity
CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED LABELING INTERFACE

4-STEP PROCESS
1. Find & label problem
2. Categorize problem
3. Rate problem severity
4. Submit work
1. Find & label problem
2. Categorize problem
3. Rate problem severity
4. Submit work

Receive another image to label & process repeats.
CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCES S

1. Verify label
3-STEP PROCESS
1. Verify label
CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS
1. Verify label
2. Verify rating
CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS
1. Verify label
2. Verify rating
3. Provide details
CROWDSOURCING ACCESSIBILITY AUDITS

WEB-BASED VERIFICATION INTERFACE

3-STEP PROCESS

1. Verify label
2. Verify rating
3. Provide details

Check for false negatives
1. Create image dataset
2. Generate ground truth labels
3. Deploy our tools to crowd
4. Compare performance to ground truth
CROWDSOURCING ACCESSIBILITY STUDY METHOD
DOWNLOAD 229 GSV IMAGES

NEW YORK
BALTIMORE
WASHINGTON DC

LOS ANGELES
1. Create image dataset

2. Generate ground truth labels
CROWDSOURCING ACCESSIBILITY STUDY METHOD
CREATE GROUND TRUTH LABELS

Bob's Labels
Sue's Labels
Alice's Labels

Majority Vote
Researcher Ground Truth
1. Create image dataset
2. Generate ground truth labels
3. Deploy our tools to crowd
3 CROWDSOURCING ACCESSIBILITY STUDY METHOD
DEPLOY TOOLS TO MECHANICAL TURK
Crowdsourcing Accessibility Study Results

**MTurk Study Statistics**

- **185** Labelers
- **7,517** Labels
- **35.2s** Label an Image

- **273** Verifiers
- **19,189** Verifications
- **10.5s** Verify an Image
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

MTURK STUDY STATISTICS

185
LABELERS

7,517
LABELS

35.2s
LABEL AN IMAGE

273
VERIFIERS

19,189
VERIFICATIONS

10.5s
VERIFY AN IMAGE

3x as fast!
1. Create image dataset
2. Generate ground truth labels
3. Deploy our tools to crowd
4. Compare performance to ground truth
Are crowd workers capable of finding accessibility problems in online map imagery?
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

OVERALL LABELING ACCURACY

With one labeler per image
OVERALL LABELING ACCURACY

With one labeler per image

SIDEWALK ENDING

85%
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

OVERALL LABELING ACCURACY

With one labeler per image

<table>
<thead>
<tr>
<th>Category</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sidewalk Ending</td>
<td>85%</td>
</tr>
<tr>
<td>Missing Curb Ramps</td>
<td>79%</td>
</tr>
<tr>
<td>Surface Problem</td>
<td>77%</td>
</tr>
<tr>
<td>Object in Path</td>
<td>73%</td>
</tr>
</tbody>
</table>
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

OVERALL LABELING ACCURACY
With one labeler per image

<table>
<thead>
<tr>
<th>Category</th>
<th>Multiclass Overall</th>
<th>Binary Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sidewalk Ending</td>
<td>85%</td>
<td>78%</td>
</tr>
<tr>
<td>Missing Curb Ramps</td>
<td>79%</td>
<td>81%</td>
</tr>
<tr>
<td>Surface Problem</td>
<td>77%</td>
<td></td>
</tr>
<tr>
<td>Object in Path</td>
<td>73%</td>
<td></td>
</tr>
</tbody>
</table>

AVERAGE OVERALL ACCURACY
COMMON LABELER MISTAKES
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

COMMON LABELER MISTAKES

OVER LABELING

(i.e., tendency towards false positives)
COMMON LABELER MISTAKES

OVER LABELING
*(i.e., tendency towards false positives)*

RANDOM LABELS
*(e.g., misunderstanding, malevolence)*

CATEGORY ERRORS
*(i.e., ambiguous problem category)*
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

ACCURACY AS A FUNCTION OF LABELERS PER IMAGE

Error bars: standard error
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

ACCURACY AS A FUNCTION OF LABELERS PER IMAGE

[Bar chart showing accuracy for 1, 3, 5, 7, and 9 labelers with majority vote, with error bars indicating standard error.]

- 1 labeler: 78%
- 3 labelers (majority vote): 84%
- 5 labelers (majority vote): 87%
- 7 labelers (majority vote): 87%
- 9 labelers (majority vote): 88%

Error bars: standard error
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

ACCURACY AS A FUNCTION OF LABELERS PER IMAGE

<table>
<thead>
<tr>
<th>Labelers</th>
<th>Multiclass Average</th>
<th>Binary Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>78%</td>
<td>81%</td>
</tr>
<tr>
<td>3 (majority vote)</td>
<td>84%</td>
<td>90%</td>
</tr>
<tr>
<td>5 (majority vote)</td>
<td>87%</td>
<td>91%</td>
</tr>
<tr>
<td>7 (majority vote)</td>
<td>87%</td>
<td>90%</td>
</tr>
<tr>
<td>9 (majority vote)</td>
<td>88%</td>
<td>90%</td>
</tr>
</tbody>
</table>

Error bars: standard error
CROWDSOURCING ACCESSIBILITY STUDY RESULTS

ACCURACY WITH CROWD VERIFICATION

- **Average Accuracy (%)**
  - **1 labeler**: 75% (Multiclass), 81% (Binary)
  - **1 labeler, 3 verifiers**: 78% (Multiclass), 88% (Binary)
  - **3 labelers**: 80% (Multiclass), 89% (Binary)
  - **3 labelers, 3 verifiers**: 82% (Multiclass), 93% (Binary)
  - **5 labelers**: 82% (Multiclass), 91% (Binary)

- **Error bars**: standard error; experiments run on subset of data

**TIME COST**
With basic quality control measures, minimally trained crowd workers can find accessibility problems with an accuracy of \(~93\%\)
But this approach relied **purely on manual labor**. Can we do better?
Is online map imagery a good source for accessibility data?

Can we create interactive tools that enable crowd workers to find accessibility problems?

How can we leverage computational techniques to scale our approach?

1. Scalable Data Collection Methods

[ASSETS'12, CHI'13, HCMP'13, ASSETS'13, UIST'14, TACCESS'15, ASSETS'17, ASSSETS'18]
Tohme

遠目・Remote Eye
1. svCrawl
Web Scraper
1. svCrawl Web Scraper

2. Street Dataset

Google Street View Panoramas

3D Point-cloud Data

Top-down Google Maps Imagery

GIS Metadata

- Latitude & longitude/
- GSV image age/
- Street & city names/
- Intersection topology/
svCrawl
Web Scraper

Street View images
3D-depth maps
Top-down map images
GIS metadata

Street Dataset

Scraped Area: 11.3 km²

D.C. Baltimore Los Angeles Saskatoon

Dataset Statistics

1,086 intersections
2,877 curb ramps
647 missing curb ramps
2.2 yrs (SD=1.3) average GSV image age
1. svCrawl Web Scraper
2. Street Dataset
   - Street View images
   - 3D-depth maps
   - Top-down map images
   - GIS metadata
3. svDetect Automatic Curb Ramp Detection
1. svCrawl
   Web Scraper

2. Street Dataset
   Street View images
   3D-depth maps
   Top-down map images
   GIS metadata

3. svDetect
   Automatic Curb Ramp Detection
svCrawl Web Scraper
svDetect Automatic Curb Ramp Detection

Street View images
3D-depth maps
Top-down map images
GIS metadata

True Positive
1. svCrawl
   Web Scraper

2. Street Dataset
   - Street View images
   - 3D-depth maps
   - Top-down map images
   - GIS metadata

3. svDetect
   Automatic Curb Ramp Detection

- True Positive
- False Positive
1. svCrawl
Web Scraper

2. Street Dataset
Street View images
3D-depth maps
Top-down map images
GIS metadata

3. svDetect
Automatic Curb Ramp Detection

Street View images
False Negative
False Positive
True Positive
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svVerify
Crowd Verification

svControl
Automatic Task Allocation

Street View images
3D-depth maps
Top-down map images
GIS metadata

Predicted CV success
svCrawl: Web Scraper

svDetect: Automatic Curb Ramp Detection

svVerify: Crowd Verification

svControl: Automatic Task Allocation

svLabel: Crowd Labeling

1. svCrawl Web Scraper
   - Street View images
   - 3D-depth maps
   - Top-down map images
   - GIS metadata

2. svDetect: Automatic Curb Ramp Detection
   - Predicted CV success
   - Predicted CV failure

3. svVerify: Crowd Verification
   - svControl: Automatic Task Allocation

4. svLabel: Crowd Labeling
1. svCrawl
   Web Scraper

2. Street View images
   3D-depth maps
   Top-down map images
   GIS metadata

3. svDetect
   Automatic Curb Ramp Detection

4. svControl
   Automatic Task Allocation

5. svVerify
   Crowd Verification
1. svCrawl
   Web Scraper

2. Street Dataset
   Street View images
   3D-depth maps
   Top-down map images
   GIS metadata

3. svDetect
   Automatic Curb Ramp Detection

4. svControl
   Automatic Task Allocation

5. svVerify
   Crowd Verification

Predicted CV success
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svVerify
Crowd Verification

Street View images
3D-depth maps
Top-down map images
GIS metadata

Predicted CV success
1. svCrawl: Web Scraper

2. Street Dataset
   - Street View images
   - 3D-depth maps
   - Top-down map images
   - GIS metadata

3. svDetect: Automatic Curb Ramp Detection

4. svControl: Automatic Task Allocation

5. svVerify: Crowd Verification

Predicted CV success
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svVerify
Crowd Verification

svLabel
Crowd Labeling

Street View images
3D-depth maps
Top-down map images
GIS metadata

Predicted CV failure
svCrawl Web Scraper
svDetect Automatic Curb Ramp Detection
svVerify Crowd Verification
svControl Automatic Task Allocation
svLabel Crowd Labeling

Street View images
3D-depth maps
Top-down map images
GIS metadata
Verifiers cannot fix false negatives (i.e., they cannot add new labels)
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svVerify
Crowd Verification

svLabel
Crowd Labeling

Street View images
3D-depth maps
Top-down map images
GIS metadata

Street Dataset
1. Deformable part model (DPM)
2. Post-processing DPM
3. SVM-based classifier
DEFORMABLE PART MODEL

Felzenszwalb et al., CVPR'08, CVPR'10
AUTOMATIC CURB RAMP DETECTOR
DEFORMABLE PART MODEL

[Image of curb ramp with filters applied]

Root filter
Parts filter
Displacement cost
AUTOMATIC CURB RAMP DETECTOR
DEFORMABLE PART MODEL

<p>| | |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>True Positives</td>
<td>1</td>
</tr>
<tr>
<td>False Positives</td>
<td>12</td>
</tr>
<tr>
<td>False Negatives</td>
<td>0</td>
</tr>
</tbody>
</table>
True Positives: 1
False Positives: 12
False Negatives: 0
2. AUTOMATIC CURB RAMP DETECTOR

POST-PROCESS DPM OUTPUT

3D-POINT CLOUD TO REMOVE CURB RAMPS ABOVE GROUND
2 AUTOMATIC CURB RAMP DETECTOR
POST-PROCESS DPM OUTPUT

NON-MAXIMUM SUPPRESSION TO REMOVE OVERLAPPING DETECTIONS

<p>| | |</p>
<table>
<thead>
<tr>
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<tbody>
<tr>
<td>True Positives</td>
<td>1</td>
</tr>
<tr>
<td>False Positives</td>
<td>12</td>
</tr>
<tr>
<td>False Negatives</td>
<td>0</td>
</tr>
</tbody>
</table>
True Positives: 1
False Positives: 5
False Negatives: 0
True Positives 1
False Positives 5
False Negatives 0

SVM FILTERS DETECTIONS BASED ON SIZE, COLOR, & POSITION IN SCENE
True Positives: 6
False Positives: 11
False Negatives: 1
**True Positives**: 6

**False Positives**: 4

**False Negatives**: 1
True Positives: 6
False Positives: 4
False Negatives: 1
1. svCrawl
   Web Scraper

2. svControl
   Street Dataset
   Street View images
   3D-depth maps
   Top-down map images
   GIS metadata

3. svDetect
   Automatic Curb Ramp Detection

4. svVerify
   Crowd Verification

5. svVerify
   Crowd Verification

6. svLabel
   Crowd Labeling

svDetect
Automatic
Task Allocation
SMART TASK ALLOCATOR

**SVM TRAINED WITH 23 INPUT FEATURES**

Binary classifier trained to predict occurrence of false negatives from svDetect stage

---

**Curb Ramp Detector Output (16 Features)**

- Raw # of bounding boxes
- Descriptive stats of confidence scores
- Descriptive stats of XY-coordinates

---

**3D-Point Cloud Data (5 Features)**

- Descriptive stats of depth information (e.g., average, median, variance) of pixel depth

---

**Intersection Complexity (2 Features)**

- Cardinality (# of connected streets)
- Amount of road
VERIFICATION TOOL
Correct false positives from computer vision

Mission:
Your mission is to verify the presence of curb ramps at intersections

Progress:
You have finished 0 out of 1.

Labeled Curb Ramps:

Keyboard Shortcuts:
Arrow Keys: Navigate
Z: Zoom in
Shift + Z: Zoom out

The area of the scene you have observed:
14%
VERIFICATION TOOL
Correct false positives from computer vision

Mission:
Your mission is to verify the presence of curb ramps at intersections.

Progress:
You have finished 0 out of 1.

Labeled Curb Ramps:

Keyboard Shortcuts:
- Arrow Keys: Navigate
- Z: Zoom in
- Shift + Z: Zoom out

The area of the scene you have observed: 14%

Please enter any comments about this bus stop that may affect people with visual impairment (optional).

Submit

This study is being conducted by the University of Maryland.
Crowd Interfaces

Labeling Tool

Find and label the following:

- Explore
- Curb Ramp
- Missing Curb Ramp

Status

Mission:
Your mission is to find and label the presence and absence of curb ramps at intersections.

Progress:
You have finished 0 out of 5.

Labeled Landmarks:
You've submitted 0 curb ramp labels and 0 missing curb ramp labels.

Keyboard Shortcuts:
- ESC: Cancel drawing
- Z / Shift + Z: Zoom in / Zoom out

Observed area: 14%

Please enter any comments about this intersection that may affect people with mobility impairment (optional)

Skip
Submit
1. Generate ground truth labels
2. Train computer vision & task controller
3. Deploy Tohme to Mechanical Turk
4. Compare Tohme to baseline
TOHME EVALUATION

OVERALL RESULTS

Accuracy (%)

0% 20% 40% 60% 80% 100%

Precision  Recall  F-measure

Manual Labeling
100% bottom workflow

CV + Verification
100% top workflow

Tohme System
full tohme system
TOHME EVALUATION

OVERALL RESULTS

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
<th>F-measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manual Labeling</td>
<td>84%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CV + Verification</td>
<td>68%</td>
<td>58%</td>
<td>63%</td>
</tr>
<tr>
<td>Tohme System</td>
<td>83%</td>
<td>86%</td>
<td>84%</td>
</tr>
</tbody>
</table>

Accuracy (%)
TOHME EVALUATION

OVERALL RESULTS

Accuracy (%)

<table>
<thead>
<tr>
<th>Manual Labeling</th>
<th>CV + Verification</th>
<th>Tohme System</th>
</tr>
</thead>
<tbody>
<tr>
<td>84%</td>
<td>68%</td>
<td>83%</td>
</tr>
<tr>
<td>88%</td>
<td>58%</td>
<td>86%</td>
</tr>
<tr>
<td>86%</td>
<td>63%</td>
<td>84%</td>
</tr>
</tbody>
</table>

Precision | Recall | F-measure

100% bottom workflow

100% top workflow

full tohme system

94s PER SCENE

42s PER SCENE

81s PER SCENE

14% faster
TOHME EVALUATION

TASK CONTROLLER PERFORMANCE

1. **svCrawl**
   Web Scraper

2. **svDataset**
   Street Dataset
   - Street View images
   - 3D-depth maps
   - Top-down map images
   - GIS metadata

3. **svDetect**
   Automatic Curb Ramp Detection

4. **svControl**
   Automatic Task Allocation

5. **svVerify**
   Crowd Verification
   - 80% Scenes correctly routed

6. **svLabel**
   Crowd Labeling
   - 50% Scenes correctly routed
TOHME EVALUATION

SIMULATED PERFECT TASK CONTROLLER

svControl
Automatic Task Allocation

5

svVerify
Crowd Verification

Simulated perfect task controller

100% scenes correctly routed

OVERALL SPEEDUP INCREASES OVER MANUAL BASELINE

14% SPEEDUP

svLabel
Crowd Labeling

6

100% scenes correctly routed

27% SPEEDUP
IMPROVING DETECTION ALGORITHMS

AUTOMATIC DETECTION IS HARD
IMPROVING DETECTION ALGORITHMS

AUTOMATIC DETECTION IS HARD

Occlusion

Illumination

Viewpoint Variation

Structures Similar to Curb Ramps

Scale

Curb Ramp Design Variation
Let's create a path for everyone

How you can help
Virtually explore city streets to find and label accessibility
Audit 1000ft of Fort Stanton

Your mission is to audit 1000ft of Fort Stanton and find all the accessibility features that affect mobility impaired travelers!
PROJECT SIDEWALK

PROJECT SIDEWALK CONTRIBUTIONS

3600+ USERS

1,075 MILES

255,000+ LABELS
WHERE ARE THE (IN)ACCESSIBLE AREAS OF DC?

What are the correlates to accessibility? Census tract data, real estate pricing, school quality, park density?

144,665 CURB RAMPS
18,960 MISSING CURB RAMPS
21,584 OBSTACLES
8,468 SURFACE PROBLEMS
43,725 NO SIDEWALK
PROJECT SIDEWALK

WHAT DO YOU SEE?

21,584 OBSTACLES

8,468 SURFACE PROBLEMS

43,725 NO SIDEWALK
WHERE ARE THE HIGH SEVERITY ISSUES?

ALL LABELS

HIGH SEVERITY
(> 3 RATING)
Only 51% of users finished tutorial (avg time: ~5 mins)

Only 30% finished their first mission

Most people who complete at least one mission, complete at least one more. Stickiness?
**PROJECT SIDEWALK**

**HOW DO WE HELP USERS LABEL MORE ACCURATELY?**

Randomly sampled 54 false positives and 54 false negatives for each label type (432 total error samples analyzed). False positives shown below.

**Curb Ramps**
- 44.4% driveway transition
- 22.2% driveways
- 14.8% random

**Missing Curb Ramps**
- 29.6% house-to-curb
- 25.9% no pedestrian route
- 24.1% curb ramp exists

**Obstacles**
- 42.6% not on pedestrian route
- 37.0% space to avoid obstacle
- 9.3% wrong label type

**Surface Problems**
- 46.2% not on pedestrian route
- 32.7% incorrect label type
- 11% normal sidewalk tiling
Improving data collection methods.

Predicting work quality, better integration with computer vision, more sophisticated feedback and training.

Data/urban science questions.

What factors correlate with urban accessibility? How can we create models that allow us to compare across cities?

New applications of method.

How can we track urban accessibility changes over time? Could we create a reusable GSV-based platform to support other studies?

Creating new interactive tools.

Interactive visualizations of neighborhood accessibility, ‘smart routing’ that takes into account accessibility obstacles.

We are actively seeking collaborators on this work!
FUTURE WORK: IMPROVING DATA COLLECTION METHODS

APPLYING DEEP LEARNING METHODS TO AUTOMATIC DETECTION

Follow-up to UIST’14, published at CVPR’17.
Are there curb ramps in these pictures? Click here for more instruction.

You have verified 0 images. 50 more to go!
Are there curb ramps in these pictures? Click here for more instructions.

You have verified 0 images. 50 more to go!
A Feasibility Study of Using Google Street View and Computer Vision to Track the Evolution of Urban Accessibility

Lanise Njiokiktjien
University of Maryland, College Park
lanise@gmail.com

Zoa E. Frankel
University of Washington
zoafrankel@uw.edu

ABSTRACT

Previous work has explored methods to extract data on the accessibility of the built environment by evaluating manual labeling, computer vision, and urban data imagery. In this paper, we explore novel methods to track the evolution of urban accessibility over time. Using Google Street View, we identified features that indicate access to accessible infrastructure and then used these features to create a new dataset of accessible infrastructure over time. This new dataset supplies additional information on changes to the built environment, which can be leveraged to improve accessibility over time.

INTRODUCTION

Many urban areas are currently inaccessible for persons with disabilities. The built environment plays a significant role in facilitating or hindering accessibility, and understanding changes in the built environment over time is critical. Google Street View is a useful tool for capturing images of the built environment, but it is not without limitations. For example, images are taken at random, and may not capture all accessible features. Additionally, manual annotation of images can be time-consuming and require significant expertise.

METHODS

We developed a new dataset of accessible infrastructure over time using Google Street View images. The dataset includes images from 2007, 2009, and 2014, and uses computer vision techniques to identify accessible features. The images were then manually annotated to identify specific features, such as curb cuts and wheelchair ramps.

RESULTS

The dataset includes images from three different years, allowing for the identification of changes in accessible infrastructure over time. The images were analyzed to identify changes in the built environment, such as the addition of new accessible features or the removal of existing ones.

CONCLUSION

The study highlights the potential of using Google Street View for tracking changes in accessibility over time. The dataset provides valuable information that can be used to inform policy decisions and improve accessibility in urban areas. Future work will involve further analysis of the dataset and the development of machine learning models to automatically identify accessible features.

Key findings:

- Google Street View images provide a useful source of data on accessible infrastructure.
- Manual annotation of images is time-consuming and requires expertise.
- Computer vision techniques can be used to identify accessible features in images.

Acknowledgments

Thanks to the University of Maryland for providing funding for this research.

References


Manual Label
FUTURE WORK: CREATING NEW INTERACTIVE TOOLS

INTERACTIVELY MODELING & VISUALIZING ACCESSIBILITY

Interactively Modeling and Visualizing Neighborhood Accessibility at Scale: An Initial Study of Washington DC
Anthony J. M. Marzouk, Antonio Cárdenas, Joel E. Freundlich
University of Maryland, College Park, University of Washington, Seattle
ammarzouk@umd.edu, antonioc@umd.edu, joelf@uw.edu

ABSTRACT

Mobility indices such as walkScore count the presence and density of walkable destinations within a neighborhood. While these metrics have great intuitive appeal and many researchers attempt to incorporate accessibility-related features such as sidewalk conditions or eachapo, density teeth including a weighted portion of the population, labtop or post, we explore the initial design and implementation of neighborhood accessibility visualization tools. Current tools for representing neighborhood accessibility are limited in their visualization capabilities and do not address the lack of granularity in neighborhood accessibility statistics. With the goal of providing a reliable, high-resolution, high-impact visualization tool, we described an interactive, accessible, neighborhood accessibility visualization tool that integrates multiple accessibility levels. The tool leverages an API provided by Project Rebound, which provides access to 250,000+ people about the accessibility and location of DC neighborhoods.

Author Keywords

Urban accessibility, accessibility visualization, interactive visualization, US cities

INTRODUCTION

Walkers such as walkScore model and visualize the “walkability” of neighborhoods by measuring the presence and density of walkable destinations (e.g., grocery stores, parks, and restaurants). While these measures suggest that neighborhoods are either “walkable” or not, they do not preserve accessibility levels. Consequently, we believe that there is a significant need for accessible, high-resolution, high-impact tools that can be used to visualize neighborhood accessibility levels.

Design

We have designed a tool for visualizing neighborhood accessibility levels that utilizes the Project Rebound API to provide detailed, high-resolution neighborhood accessibility statistics. The tool allows users to interact with the map and see how accessibility levels change as they move through the neighborhood. The tool also includes a feature that allows users to compare accessibility levels across different neighborhoods.

Conclusion

In summary, our tool provides a significant improvement over existing tools for visualizing neighborhood accessibility levels. The tool is accessible, interactive, and high-resolution, and it provides a valuable tool for understanding neighborhood accessibility levels.

How important are...?

Curb ramps?

3

Smooth sidewalks?

3

Unobstructed sidewalks?

3
PROJECT SIDEWALK
OPEN SOURCE & OPEN DATA

https://github.com/ProjectSidewalk

http://projectsidewalk.io/api
Help make the world more accessible for everyone!
Join us. Email: jonf@cs.uw.edu.
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FUNDING SOURCES

NSF #1302338, Google, IBM
PI Froehlich, Co-PI David Jacobs
PROJECT SIDEWALK: CURRENT TEAM

Jon E. Froehlich  
Feb 2012 – Present  
Associate Professor

Mikey Saugstad  
May 2012 – Present  
Research Scientist

Manaswi Saha  
Oct 2016 – Present  
PhD Student

Anthony Li  
Aug 2018 – Present  
Undergrad

Aileen Zeng  
May 2018 – Present  
Undergrad

PROJECT SIDEWALK: PAST MEMBERS

Marcus Arnalachandran  
High School Student

Shiven Bhatt  
Jan 2016 – Aug 2016  
High School Student

Teja Maddali  
May 2016 – Dec 2016  
PhD Student

Johann Miller  
Aug 2016 – Dec 2017  
Undergrad

Sarah Smolen  
Aug 2017 – Dec 2017  
Undergrad

Steven Bower  
Jan 2017 – Aug 2017  
Undergrad

Ryan Helland  
Jan 2017 – Aug 2017  
High School Student

Aditya Dash  
Jun 2017 – Aug 2017  
Undergrad

Chirag Shankar  
Jul 2017 – Aug 2017  
Undergrad

David Jacobs  
Aug 2017 – Aug 2017  
Professor

Sage Chen  
May 2017 – Jul 2017  
Undergrad

Maria Furman  
Dec 2016 – May 2017  
Undergrad

Ji Hyuk Bae  
Jan 2017 – Mar 2017  
Undergrad

Soheil Behneshad  
PhD Student

Kotare Hara  
May 2017 – Dec 2017  
Undergrad

Ladan Najafzadeh  
Jun 2016 – Dec 2016  
MB Student

Danit Zadorozhnyy  
May 2016 – Aug 2016  
Undergrad

Zachary Lawrence  
Jan 2015 – Dec 2016  
Undergrad

Alexander Zhang  
Jan 2015 – Dec 2016  
Undergrad

Christine Chan  
May 2015 – Aug 2015  
Undergrad

Niles Rogoff  
Jan 2015 – Aug 2015  
High School Student

Anthony Li  
Jun 2016 – Dec 2016  
Undergrad

Robert Moore  
Jan 2015 – Dec 2016  
Undergrad

Jin Sun  
Jun 2016 – Aug 2016  
Undergrad

Sean Pannella  
Jan 2015 – Dec 2015  
Undergrad

Victoria Li  
Undergrad

Noa Chazan  
May 2015 – Aug 2015  
Undergrad
Help make the world more accessible for everyone!
Join us. Email: jonf@cs.uw.edu.