Characterizing Physical World Accessibility at Scale
Combining Google Street View, Crowdsourcing, and Automated Methods to Collect Accessibility Data about the Built Environment

Kotaro Hara
The Americans with Disabilities Act mandates that new constructions and alterations of the built environment are to be accessible for everyone.
The inequality of sidewalks

By Emily Badger

January 15

By Emily Badger
30.6 million U.S. adults with mobility impairment
15.2 million use an assistive mobility aid
Missing Curb Ramp

Obstacle

Surface Problem

No Sidewalk

Meyers et al. [Soc. Sci. & Med. 2002], Rimmer et al. [AJPM 2004]
The problem is also that there are few mechanisms to determine accessible areas of a city a priori.
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
Address: 123 Broadway Ave NW

This address received an accessibility score of 67 primarily because 28% of nearby intersections lack curb cuts, 20% roads lack sidewalks on both sides, and a lack of an accessible grocery store within 0.5 miles.
Routing for: Manual Wheelchair

1st of 3 Suggested Routes
16 minutes, 0.7 miles, 1 obstacle

Route 1

Route 2

Accessibility-aware Navigation

Surface Problem
Avg Severity: 3.6 (Hard to Pass)
Recent Comments:
“Obstacle is passable in a manual chair but not in a motorized chair”
Our vision is to design methods to scalably collect street-level accessibility data that enables technologies that support mobility impaired people to navigate the physical environment.
Traditional Walkability Audits

Walkability Audit
Wake County, North Carolina

Walkability Audit
Wake County, North Carolina

Safe Routes to School Walkability Audit
Rock Hill, South Carolina

Background
## Safe Routes to School Walkability Audit

### Rock Hill, South Carolina

### Wake County, North Carolina

### Traditional Walkability Audits

#### Background

*Time consuming, expensive, and requires on-site audit*

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## How walkable is your community?

<table>
<thead>
<tr>
<th>Location of walk</th>
<th>Rating Scale:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2 3 4 5 6</td>
</tr>
</tbody>
</table>

1. **Did you have room to walk?**
   - Yes
   - No

   - Sidewalks or paths started and stopped
   - Sidewalks were broken or cracked
   - Sidewalks were blocked with poles, signs, flowerpots, etc.
   - No sidewalks, paths or shoulders
   - Too much traffic
   - Something else

   Rating: (circle one) 1 2 3 4 5 6

2. **Was it easy to cross streets?**
   - Yes
   - No

   - Road was too wide
   - Traffic signals made us wait too long or did not give us enough time to cross
   - Needed striped crosswalks or traffic signals
   - Parked cars blocked our view of traffic
   - Fumes or plumes blocked our view of traffic
   - Needed curb ramps or ramps needed repair
   - Something else

   Rating: (circle one) 1 2 3 4 5 6

3. **Did drivers behave well?**
   - Yes
   - No

   - Backed out of driveways without looking
   - Did not yield to people crossing the street
   - Turned into the street when crossing the street
   - Driver too fast
   - Speed up to make it through traffic lights or drive through traffic lights
   - Something else

   Rating: (circle one) 1 2 3 4 5 6

4. **Was it easy to follow safety rules?**

   **Could you and your child...**
   - Yes
   - No

   - Cross at crosswalks or where you could see and be seen by drivers?
   - Stop and look left, right and then left again before crossing streets?
   - Walk on sidewalks or shoulders facing traffic where there were no sidewalks?
   - Cross with the light?

   Rating: (circle one) 1 2 3 4 5 6

5. **Was your walk pleasant?**
   - Yes
   - No

   - Some unpleasant things:
     - Needed more grass, flowers, or trees
     - Scary dogs
     - Scary people
     - Not well lighted
     - Dirty, lots of litter or trash
     - Something else

   Rating: (circle one) 1 2 3 4 5 6

---

Now that you’ve identified the problems, go to the next page to find out how to fix them.
Mobile Reporting Solutions

Background

http://www1.nyc.gov/311/index.page
Background

Mobile Reporting Solutions

[Image of mobile application interface with options for selecting complaints such as Broken Sidewalk, Fire Hydrant, Damaged Tree, New Tree, etc.]
Similar to physical audits, these tools are built for *in situ* reporting and do not support remote, virtual inquiry—which *limits scalability*. 

Not designed for *accessibility data collection*.
Mark & Find Accessible Businesses

Focuses on businesses rather than streets/sidewalks

Model is still to report on places you’ve visited
Our Approach: Remotely collect street-level accessibility information from Google Street View (GSV) using crowdsourcing and computation.
A Feasibility Study of Crowdsourcing a View to Determine Sidewalk Accessibility
Kotaro Hara, Victoria Le, J.E. Froehlich
Department of Computer Science, University of Maryland, College Park
(kotaro, jonl, vsf)@cs.umd.edu; vmle@umd.edu

ABSTRACT
We explore the feasibility of using crowd workers from Amazon’s Mechanical Turk to identify and rank sidewalk accessibility issues encountered by people who are visually impaired. To our knowledge, this study is the first to test the feasibility of crowdsourcing sidewalk accessibility issues. We identify 100 locations and estimate their accessibility by analyzing Google Street View images and applying machine learning to identify features that are likely to be encountered by visually impaired people. With the growing number of visually impaired users of Google Street View, this type of crowdsourcing is likely to become more popular in the future.

Categorization and Subject Descriptors
D.2.2 [Computer and Information Science]: Artificial Intelligence, Natural Language Processing

Keywords
Crowdsourcing, accessibility, Google Street View, accessible urban navigation, Mechanical Turk

1. INTRODUCTION
The availability and usability of sidewalks can significantly impact how and where people travel in urban environments. Sidewalks with surface cracks, buckled concrete, missing curbs, or other issues can pose considerable accessibility challenges to people with mobility or vision impairments [1,2]. Traditionally, these issues have been uncovered via in-person sidewalk quality assessments that have been time-intensive and costly, often eliminating any analysis that might be useful in informing the design of new sidewalks.

Crowdsourcing Accessibility Data from Google Street View

Early Work

Combining Crowdsourcing and Google Street View to Identify Street-level Accessibility Problems
Kotaro Hara, Victoria Le, J.E. Froehlich
Human-Computer Interaction Lab (HCIL)
Computer Science Department, University of Maryland, College Park
(kotaro, jonl)@cs.umd.edu; vmle@umd.edu

ABSTRACT
Combining crowd sourcing and Google Street View imagery to identify sidewalk accessibility problems could improve the development of accessible urban navigation systems. In this paper, we describe a feasibility study to determine the potential of crowd sourcing to identify sidewalk accessibility problems. Our goal is to develop a method to identify and rank sidewalk accessibility issues encountered by people who are visually impaired. This is the first study to explore the feasibility of crowd sourcing sidewalk accessibility problems.

Categorization and Subject Descriptors
K.7.1 [Information Interfaces and Presentation]: User Interfaces, Design, Empirical Studies, Human Factors

General Terms
Measurement, Design, Experimentation, Human Factors

1. INTRODUCTION
Google is the most widely used search engine, and their Google Street View service is the most popular 360-degree street view service. As more and more people are discovering the benefits of Google Street View, we are starting to see the potential of crowd sourcing sidewalk accessibility problems using Google Street View imagery.

Improving Public Transit Accessibility for Blind Riders by Crowdsourcing Bus Stop Landmark Locations with Google Street View
Kotaro Hara1, Shari Azarnejad2, Robert Mooney3, Megan Campbell2, Cynthia Lam-Himlin4, Vicki Le5, 6

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ABSTRACT
Public transportation systems are critical to the everyday lives of many people. However, they often lack information that is crucial for the cooperation and independence of blind riders. We developed an accessible public transportation system that uses crowd sourcing to identify landmarks at bus stops. The system allows blind riders to access information about bus stops, including images of the bus stop, street view images, and landmarks.

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What accessibility problems exist in this image?
Labeling Interface

Early Work
Early Work

Labeling Interface
Crowdsourced Data Accuracy

We could collect street-level accessibility data from static Google Street View using crowdsourcing with **81% accuracy** and this figure went up to **93% with majority voting**

Sole reliance on paid-crowdsourcing limits the method’s scalability.
Scalable Data Collection Methods

Volunteered Data Collection

Semi-automated Data Collection
Related Work: Quantifying Neighborhood Environment Using Computer Vision

Related Work: Quantifying Neighborhood Environment Using Computer Vision

Related Work: Quantifying Neighborhood Environment Using Computer Vision

We need more granular information to understand which sidewalks are accessible/inaccessible and why.
CrowdFlow: Integrating Mechanical Turk for Speed-Centric Visual Recognition with Humans and Machines

Hao Su, Jia Deng, Li Fei-Fei

Abstract

Humans and machines have competing strengths for tasks such as natural language processing and image analysis. While machines are good at finding patterns in massive amounts of data, humans are better at understanding context and identifying novel situations. In recent years, there has been a great deal of interest in combining the strength of humans and machines to improve the performance and robustness of computer vision systems. One approach is to use crowdsourcing, which is the practice of involving non-expert human subjects in the design, development, and operation of computer systems. This paper proposes a new method for integrating human expertise into machine learning systems through a novel system called CrowdFlow. CrowdFlow combines the strengths of human workers with machine learning algorithms to improve the accuracy and reliability of visual recognition tasks. Through a series of experiments, we demonstrate the effectiveness of CrowdFlow in a variety of challenging scenarios. We believe that CrowdFlow has the potential to significantly improve the performance of computer vision systems and open up new possibilities for using human expertise in the design of intelligent systems.

1 Introduction

The task of visual object detection is one of the fundamental problems in computer vision, and it has been widely studied in recent years. However, despite the progress made in this area, there are still many challenges that need to be addressed.

There are several factors that make visual object detection a challenging problem. First, the task involves identifying and localizing objects in images, which requires a high level of visual perception and understanding. Second, the task is inherently ill-defined, as objects can have a wide variety of appearances and context-dependent associations. Finally, the task is often ambiguous, as objects can overlap or be partially occluded.

To address these challenges, we propose a novel system called CrowdFlow that integrates human expertise into machine learning algorithms. CrowdFlow combines the strengths of human workers with machine learning algorithms to improve the accuracy and reliability of visual recognition tasks. Through a series of experiments, we demonstrate the effectiveness of CrowdFlow in a variety of challenging scenarios. We believe that CrowdFlow has the potential to significantly improve the performance of computer vision systems and open up new possibilities for using human expertise in the design of intelligent systems.
Related Work: Object Detection with Human-in-the-Loop

Task: Detect all the bottles

Step 1: An object detection algorithm detects bottles

Step 2: Humans verify the object detection outputs

More accurate compared to computer vision alone and cheaper than human labeling
Adaptive Workflow for Optimizing Efficiency

Varying the number of workers to recruit depending on task difficulty
[Kamar et al. 2012; Welinder and Perona 2010]

Assigning stronger workers to harder tasks
[Dai et al. 2011]

Reducing the tasks that require human work
[Deng et al. 2014; Jain, Grauman, and Betke 2016]

Changing task interface based on worker characteristics
[Jain and Grauman 2013, Lin et al. 2012, Russakovsky et al. 2015]
Tohme 遠目 • Remote Eye

Computer vision automatically finds curb ramps
Without curb cuts, **people with ambulatory disabilities simply cannot navigate the city.**

Kinney v. Yerusalim, 1993
3rd Circuit, Court of Appeals
Curb Ramps are Visually Salient
svCrawl
Web Scraper

3D Depth Map
GIS Metadata (e.g., topological data)
Top down map images
Street View images

Dataset
Tohme
遠目・Remote Eye

svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

Dataset
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

Dataset

Did our computer vision algorithm perform well?

svControl
Automatic Task Allocation
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

Dataset

svControl
Automatic Task Allocation

svVerify
Manual Label Verification
How do we define computer vision failure?

Correct detection

False positive detections

False Negative Error = Computer Vision Failure

Because asking humans to label missed curb ramps is much more expensive than asking to verify
A feature vector used to in the workflow controller

- Complexity: 0.14
- Cardinality: 0.33
- Depth: 0.21
- CV: 0.22
Pass!

Complexity: 0.14
Cardinality: 0.33
Depth: 0.21
CV: 0.22
Tohme
遠目・Remote Eye
Tohme
遠目・Remote Eye

Complexity: 0.82
Cardinality: 0.25
Depth: 0.96
CV: 0.54
Remote Eye

Complexity: 0.82
Cardinality: 0.25
Depth: 0.96
CV: 0.54
svCrawl
Web Scraper

Dataset

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svLabel
Manual Labeling

svVerify
Manual Label Verification

Tohme
遠目·Remote Eye
Street View Images

We collected images from intersections because that’s where we find curb ramps.
Street View Images

Point-cloud Data
Scraper

Street View Images

Point-cloud Data

Metadata
(e.g., street topology)

- Links: [
  - {
    yawDeg: "189.97",
    panoId: "WDH0FV_F6s9QEOXFMwktOg",
    road_args: "0x80f6f872",
    description: "Morse St NE"
  },
  - {
    yawDeg: "299.71",
    panoId: "UCZmw_4Q1SrGAiJoEa9fmg",
    road_args: "0x80f6f872",
    description: "Morse St NE"
  }
]
Scraper

Street View Images

Point-cloud Data

Metadata (e.g., street topology)

Top-down Google Maps Imagery
Scraper

Street View Images

Point-cloud Data

Metadata (e.g., street topology)

Top-down Google Maps Imagery

Used to train curb ramp detector and workflow controller
Scraper

Street View Images

Point-cloud Data

Metadata (e.g., street topology)

Top-down Google Maps Imagery
Washington D.C.  Baltimore  Los Angeles  Saskatoon

Total Area: 11.3 km²
Intersections: 1,086
Curb Ramps: 2,877
Missing Curb Ramps: 647
Avg. GSV Data Age: 2.2 yr*

* At the time of downloading data in summer 2013
Tohme
遠目・Remote Eye

svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svLabel
Manual Labeling

svVerify
Manual Label Verification

Dataset
Ground Truth Curb Ramp Dataset

2 researchers labeled curb ramps in our dataset

2,877 curb ramp labels (Avg. = 2.6 per intersection)
Tohme
遠目・Remote Eye

svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svLabel
Manual Labeling

svVerify
Manual Label Verification

Dataset
Automatic Curb Ramp Detection

1. Curb ramp detection with Deformable Part Model

2. Post-processing to filter out errors

3. SVM-based classification for output refinement
Deformable Part Models
Felzenszwalb et al. 2008

http://www.cs.berkeley.edu/~rbg/latent/
Automatic Curb Ramp Detection

Deformable Part Models
Felzenszwalb et al. 2008

Root filter
Parts filter
Displacement cost

http://www.cs.berkeley.edu/~rgb/latent/
Automatic Curb Ramp Detection
Detected Labels
Stage 1: Deformable Part Model
Sliding window detection with deformable part model

Multiple redundant detection boxes

<p>| | |</p>
<table>
<thead>
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<tbody>
<tr>
<td>Correct</td>
<td>1</td>
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<tr>
<td>False Positive</td>
<td>12</td>
</tr>
<tr>
<td>Miss</td>
<td>0</td>
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</table>
Curb ramps shouldn’t be in the sky or on roofs

Detected Labels
Stage 1: Deformable Part Model
Sliding window detection with deformable part model

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Detected Labels

Stage 2: Post-processing

Rejects errors using 3D data and applies non-maxima suppression
Detected Labels
Stage 2: Post-processing
Rejects errors using 3D data and applies non-maxima suppression

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<td>5</td>
<td></td>
</tr>
<tr>
<td>Miss</td>
<td>0</td>
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</tbody>
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Automatic Curb Ramp Detection

Detected Labels
Stage 3: SVM-based Refinement
Takes size, color, and position and further filters out false detections

- **Correct**: 1
- **False Positive**: 5
- **Miss**: 0

Filter out labels based on their size, color, and position.
Detected Labels
Stage 3: SVM-based Refinement
Takes size, color, and position and further filters out false detections
Detected Labels

Stage 1: Deformable Part Model

Sliding window detection with deformable part model

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Stage 2: Post-processing
Rejects errors using 3D data and applies non-maxima suppression

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<tr>
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<th>6</th>
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<tr>
<td>False Positive</td>
<td>4</td>
</tr>
<tr>
<td>Miss</td>
<td>1</td>
</tr>
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</table>
Automatic Curb Ramp Detection Accuracy

Used two-fold cross validation to evaluate CV sub-system
**Computer Vision Sub-System Results**

- **Precision**: Higher, less false positives
- **Recall**: Higher, less false negatives
Goal: maximize area under curve
More than 20% of curb ramps were missed

AUC_{Stage 1} = 0.48

AUC_{Stage 2} = 0.50

AUC_{Stage 3} = 0.53

COMPUTER VISION SUB-SYSTEM RESULTS
Computer vision alone is not sufficient to accurately find curb ramps.

Pr, Re = 84%, 88%
1 turker

Graph showing the precision and recall for different stages of computer vision sub-system results:
- Stage 1: DPM
- Stage 2: Post-processing
- Stage 3: SVM
Curb Ramp Detection is a Hard Problem

Occlusion
Occlusion
Curb Ramp Detection is a Hard Problem
Illumination
Curb Ramp Detection is a Hard Problem

Occlusion

Illumination

Scale
Curb Ramp Detection is a Hard Problem
View Point Variation
Curb Ramp Detection is a Hard Problem

Occlusion

Illumination

Scale

Viewpoint Variation

Structures Similar to Curb Ramps
Structures Similar to Curb Ramps
Curb Ramp Detection is a Hard Problem

- Occlusion
- Illumination
- Scale
- Viewpoint Variation
- Structures Similar to Curb Ramps
- Curb Ramp Design Variation
Curb Ramp Design Variation
A number of streets from metadata

Depth information for a road width and variance in distance

Top-down images to assess complexity of an intersection

A number of detections and confidence values
Automatic Task Allocation | Features to Assess Scene Difficulty for CV

A number of street from metadata

Depth information for a road width and variance in distance

Top-down images to assess complexity of an intersection

A number of detections and confidence values
Finding curb ramps on distant sidewalks is difficult; they look smaller (i.e., scaling issue)
A number of streets from metadata

Depth information for a road width and variance in distance

Top-down images to assess complexity of an intersection

A number of detections and confidence values
As a proxy for intersection complexity, we count the number of black pixels:

more black pixels = more complex intersection (i.e., more viewpoint variation)
Automatic Task Allocation | Features to Assess Scene Difficulty for CV

A number of streets from metadata

Depth information for a road width and variance in distance

Top-down images to assess complexity of an intersection

CV Output: A number of detections and confidence values
Binary Classification
Binary classifier to detect false-negatives
Manual Labeling | Labeling Interface

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%
Help Us Improve Street Accessibility

Hi, we're exploring new ways to find accessibility problems in cities, and we need your help! In this task, your mission is to label curb ramps and missing curb ramps in Google Street View. Curb ramps are very important--without them, people in wheelchairs cannot move about the city.

An image of curb ramps at an intersection.

A lack of a curb ramp at this corner obstruct wheelchair users from getting on and off the sidewalk.

We'll begin with a short, interactive tutorial to get you started! Thanks for your help in improving the accessibility of cities.
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:
- Curb Ramps: 3
- Missing Curb Ramps: 0

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: 75%
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svControl
Automatic Task Allocation

svVerify
Manual Label Verification

svLabel
Manual Labeling

Tohme
遠目 Remote Eye

Dataset
svCrawl
Web Scraper

svDetect
Automatic Curb Ramp Detection

svLabel
Manual Labeling

svControl
Automatic Task Allocation

svVerify
Manual Label Verification

Tohme
遠目・Remote Eye
Manual Label Verification

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.
Manual Label Verification

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.
Study Method: Conditions

- Manual labeling without smart task allocation
- CV + Verification without smart task allocation
- VS. Tohme ('Remote Eye')
Study Method: Measures

- Accuracy
- Task Completion Time
Study Method: Approach

We recruited workers from Amazon Mechanical Turk to work on labeling tasks and verification tasks.

We used 1,046 GSV images.
Evaluation

We evaluated the result with Monte Carlo simulation

**Labeling Tasks**
- # of distinct turkers: 242
- # of tasks completed: 6,350

**Verification Tasks**
- # of distinct turkers: 161
- # of tasks completed: 4,820
Accuracy Measures (%)

**ACCURACY**

Higher is better

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

- Manual Labeling
- CV and Manual Verification
- Tohme ・ Remote Eye

Cost (Time)

Lower is better

0 20 40 60 80 100

- Manual Labeling
- CV and Manual Verification
- Tohme ・ Remote Eye

Error bars are standard deviations.
Evaluation | Labeling Accuracy and Time Cost

**Accuracy**

- Precision: 84%, 88%, 86%
- Recall: 68%, 58%, 63%
- F-measure: 83%, 86%, 84%

Error bars are standard deviations.

**Cost (Time)**

- Task Completion Time / Scene (s):
  - Manual Labeling: 94 s
  - CV and Manual Verification: 42 s
  - Tohme: 81 s

Error bars are standard deviations.
Evaluation | Labeling Accuracy and Time Cost

**ACCURACY**

- Precision: 84% ± 2%, 88% ± 2%, 86% ± 2%
- Recall: 68% ± 2%, 58% ± 2%, 63% ± 2%
- F-measure: 83% ± 2%, 86% ± 2%, 84% ± 2%

**COST (TIME)**

- Task Completion Time / Scene (s): 94 ± 13%, 81 ± 13%

Error bars are standard deviations.

A 13% reduction in cost.
Example Labels from Manual Labeling
This is a driveway. Not a curb ramp.
Examples Labels from CV + Verification
Automatic Detection

False detection
Automatic Detection + Human Verification
We developed a method that combines crowdsourcing and computation that increased accessibility data collection efficiency without losing accuracy.
Back of Envelope Calculation
How long would it take to audit a city?

DC Total Street Distance: 1,238 mi
Audit Speed: 7.9 mi / hour

Estimated Total Time-cost: 157 hour ($1.1k)

Estimated Total Time-cost with automation: 137 hour

I think we can do better than this 😊
Future Work: Improving Detection Accuracy

Context integration & scene understanding
Using 3D-data for mensuration
Future Work: Reacting to Changes

Using image dataset that is updated frequently, can we identify dynamic accessibility features like constructions?
Future Work: Research Beyond Sidewalk Accessibility

- Bus stop accessibility
- Urban vegetation
- Public health (e.g., cleanliness)
- Urban planning (e.g., bicycle roads)

Hara et al. [ASSETS 2013, TACCESS 2015]
Access Score\textsubscript{beta} in Action

Find out about neighborhood accessibility of DC! Here, accessible neighborhoods are colored in green and inaccessible neighborhoods are colored in red.

If some accessibility features affect your mobility more than the others, use the slider below to adjust the significance of each accessibility feature!

Note, we don’t have enough data to reliably calculate Access Score for some neighborhoods (yet). Wanna help us improve it? Participate in accessibility audit!

<table>
<thead>
<tr>
<th>Significance</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Curb Ramp</td>
<td></td>
</tr>
<tr>
<td>No Curb Ramp</td>
<td></td>
</tr>
<tr>
<td>Obstacle</td>
<td></td>
</tr>
<tr>
<td>Surface Problem</td>
<td></td>
</tr>
</tbody>
</table>

Future Work: Application Development
sidewalk.umiacs.umd.edu/demo
Collaborators

Advisor
Jon E. Froehlich

Professors | Researchers
Shiri Azencot and David Jacobs

Students
Cynthia L. Bennett, Megan Campbell, Christine Chan, Jonah Chazan, Vicki Le, Anthony Li, Kelly Minckler, Zachary Lawrence, Robert Moore, Rochelle H. Ng, Sean Pannella, Niles Rogoff, Manaswi Saha, Soheil Sehnezhad, Jin Sun, and Alex Zhang,
Thank you!
Kotaro Hara | @kotarohara_en

sidewalk.umiacs.umd.edu