

Augmenting Reality via Client/Cloud Platforms

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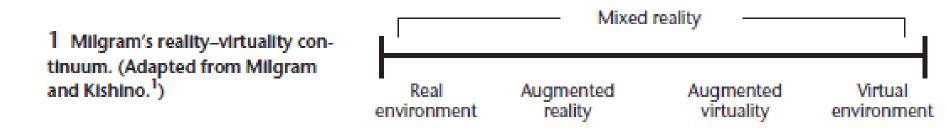


- What is Augmented Reality (AR)?
- Why now?
- Current examples and apps
- Image based localization for AR apps
 - Indoor and outdoor
- Future directions of research

What is Augmented Reality?



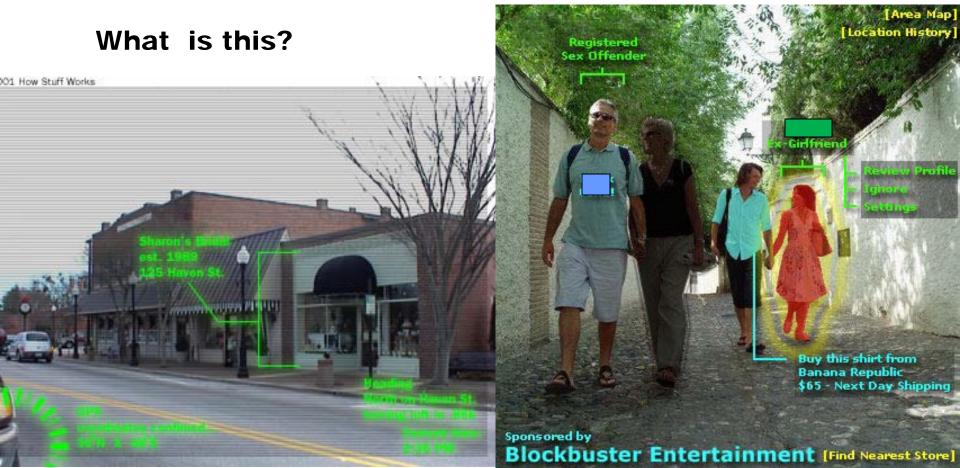
- Enhance or augment real/actual world to create a more satisfying user experience/perception:
- Joining of virtual and actual reality



"The real world is way too boring for many people. By making the real world a playground for the virtual world, we can make the real world much more interesting." -Daniel Sánchez-Crespo, Novarama **AR Helps with Questions like**



Who are these people?



Familiar Real World Examples of AR



Heads up Display



Sports Broadcasting



Actual Applications ...



Word Lens: Real time Translation; OCR



Use GPS & orientation sensor

B2.0W 91.0W 97.0W 97.0W 110.0W 100.0W 100.0W

Dish-pointer for Satellite



Layar: Generalized AR platform

Yelp: Local reviews

Google Goggles

- Google Goggle uses imagery for visual search, but:
 - Works well with famous landmarks
 - Doesn't generalize to "typical streets"
- Most AR apps today leave a lot to be desired

Google Goggles in Action

Click the icons below to see the different ways Google Goggles can be used.



Available on phones that run Android 1.6+ (i.e. Donut or Eclair)



Why now?

- Prevalence of mobile/handheld devices e.g. smart phones with lots of sensors:
 - Cameras
 - Coarse orientation measurement sensors:
 - Landscape vs. portrait on i-Phone
 - Coarse GPS
 - Coarse accelerometers
 - Game applications









1995



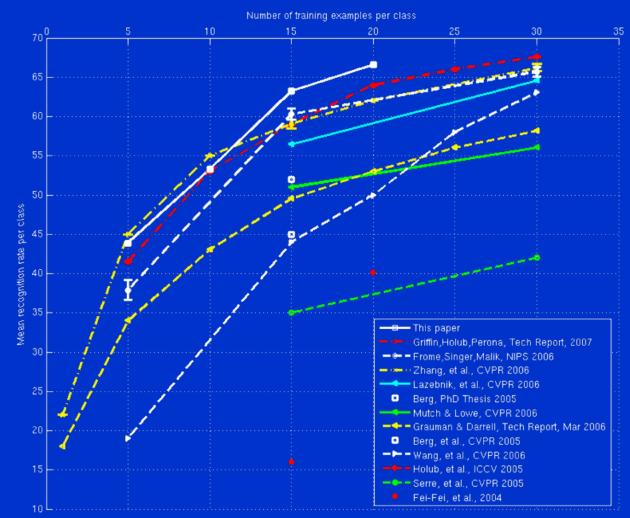




Why now ? (2)



- CPU cycles are more abundant and cheaper than ever
 - Cloud computing
- Wireless networks are getting faster
- Recognition performance improving by leaps and bounds in the last 6 years





- Suite of sensors to sense/recognize the environment & to localize user:
 - Camera
 - GPS & orientation sensors
- Algorithms to process sensor data → signal/image processing, vision, recognition, ...
- Databases to look up meta data associated with user's environment → cloud storage
- Networks to communicate meta data to the user
 intermittent connectivity
- Present the data to the user

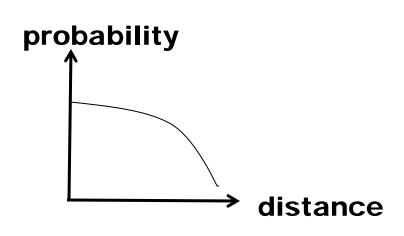
 User interface, rendering, visualization

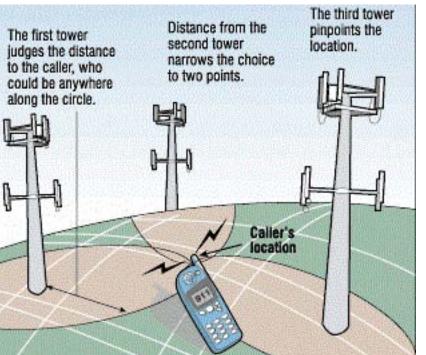
Localization & Tracking

- Google's Schmidt: Location, mobile ads will revolutionize commerce Mobile World Congress, Barcelona, Spain, Feb. 14th, 2010; "A billion dollar business right in front of us."
- Localization:
 - Means position *and* orientation
 - Indoor and outdoor
- Using GPS for outdoors:
 - Does not provide orientation.
 - Not accurate for most AR apps
 - Even differential GPS not accurate enough
 - Need pixel level accuracy
 - GPS satellites not always visible to mobile
 - Need to see three satellites
 - Urban environments with tall buildings, e.g. Manhattan
 - How about cell tower triangulation?

Cell Tower Triangualation

- Mandate by FCC:
 - 911 emergency services
 - Law enforcement
 - 67% of phones must be localized within 50 meters
 - 95% within 150 meters

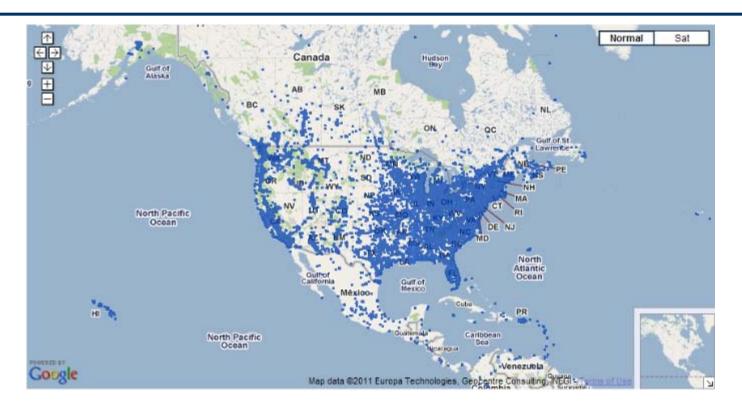






How about WiFi?





- Dense urban environments with tall buildings likely to have great WiFi coverage:
 - Accuracy not large enough for AR applications
 - Privacy issues

Image Data Bases (dB) & Localization

- Drawbacks of existing approaches:
 - Not accurate to pixel level
 - Do not provide orientation
- Use images to overlay info/tags/meta-data on viewfinders to achieve pixel level accuracy
 - Image based localization
- Need Large image databases:
 - Street View from Google,
 - Bing maps from Microsoft,
 - Earthmine, etc





Mass scale image acquisition systems





Earthmine





Google StreetView Picture for the Intersection of Hearst and LaLoma, Berkeley, CA

😔 Internet

Mahsn-m..

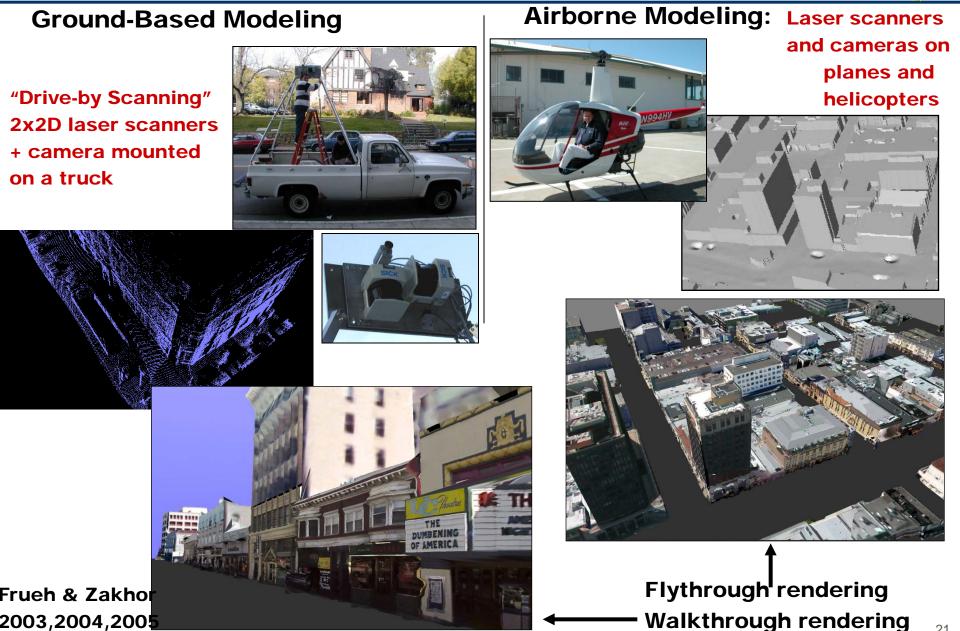
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Google Earth 3D model of NY

3D Model Construction Project at UC Berkeley: 2000 - 2006





📚 Google Earth

 File Edit View Tools Add Help
 Satellite Picture of downtown Berkeley

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Image @ 2007 TerraMetrics

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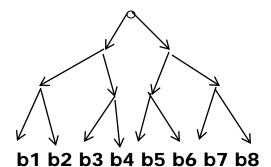
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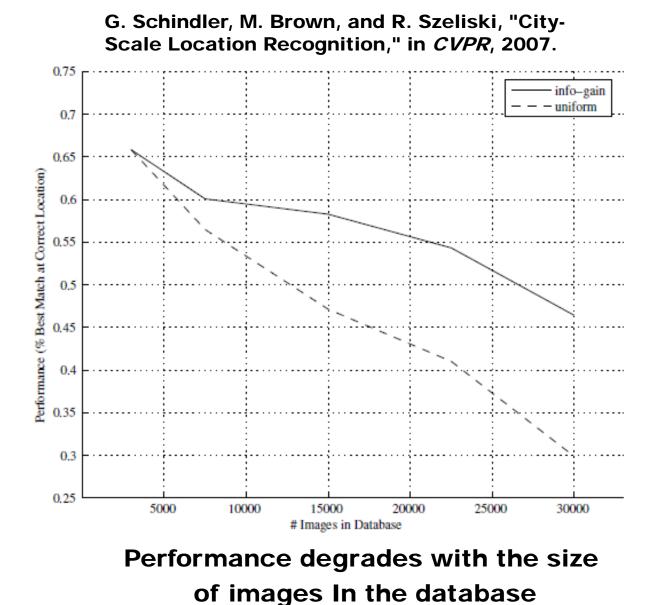
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How to use Image Database to "Localize"



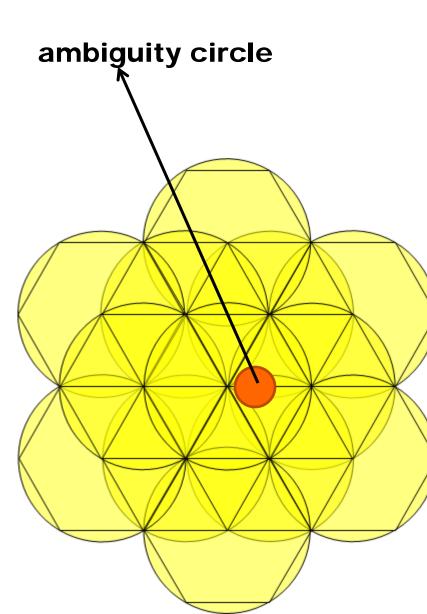
- Compute features of images in the dB and the query image
 - Bag of words model
- Train a vocabulary tree or K-D tree using all the features from dB images
 - Quantizes features that are close to each other in the same "bin"
- Input the features of the query image to the "tree"
- Score for each dB image:
 - number of "matched features" to the query
- Find largest score dB image



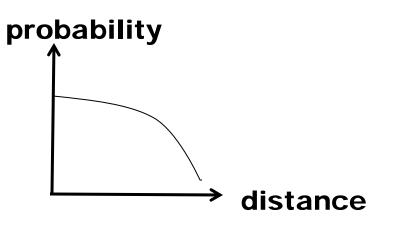


Divide and Conquer → Scalable



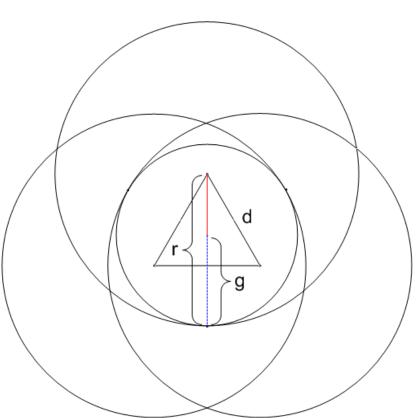


- Divide a large geographic area into overlapping circular "cells"
 - Centered at vertices of hexagonal lattice
 - Similar to "handoff" in wireless carriers
- Each cell has its own k-d tree
- Coarse location reported by cell phone:
 - GPS or cell tower triangulation
 - Actual location is within *ambiguity circle* centered around reported location
 - Probability distribution function from FCC



Optimal Geometry for the Cells





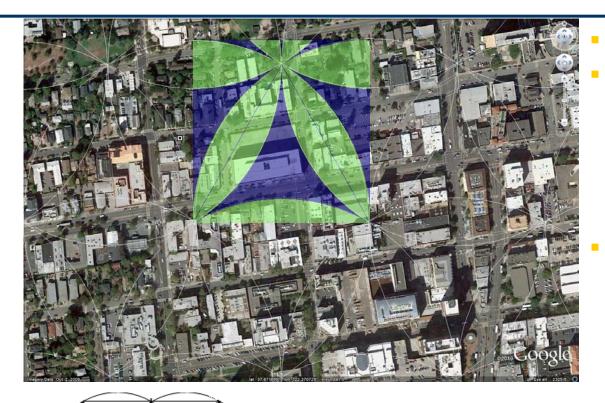
- Cell radius R;
- Ambiguity circle radius G;
- Distance between center of cells: D →Overlap
- To ensure entire ambiguity circle lies inside at least ONE cell:

 $d \le \sqrt{3}(r-g)$

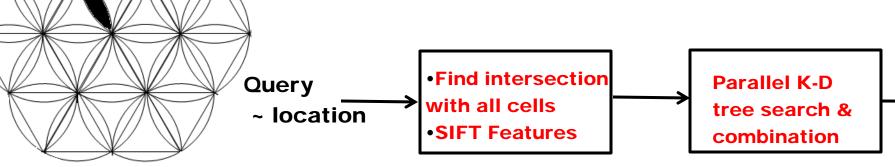
- Can get away with just ONE cell search

Combine Results of Multiple Cells



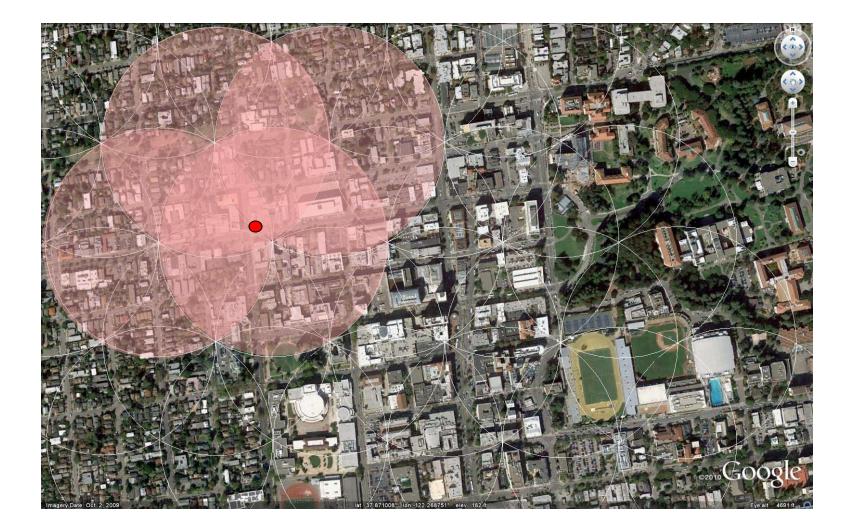


- Assume D= R
- Each image is in
 - 4 cells if in "petal", 3 cells if not in "petal"
 - With zero ambiguity, can combine 3 to 4 cells to improve results
- Ambiguity circle can overlap with 3 to 9 cell
 - Search all cells Amb. Cir. intersects with, even if matched image in only 3 to 4 cells.
- Combine the scores of dB images from various cells



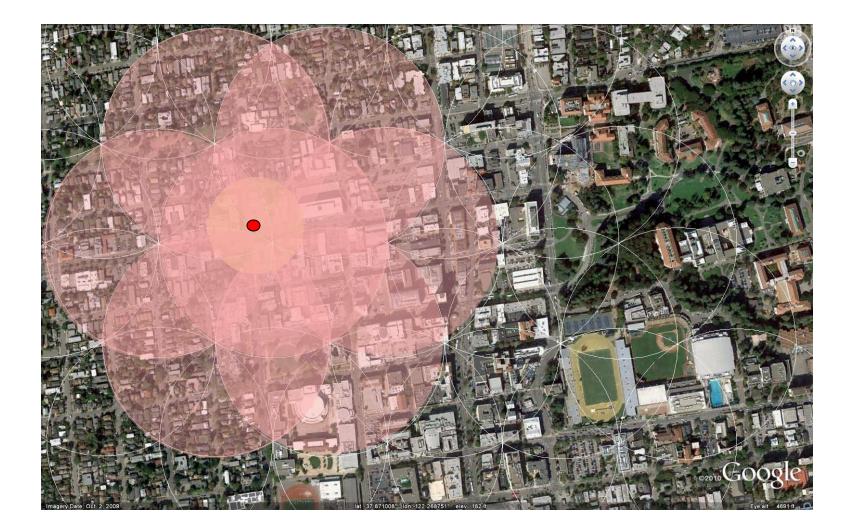
Example: no location ambiguity



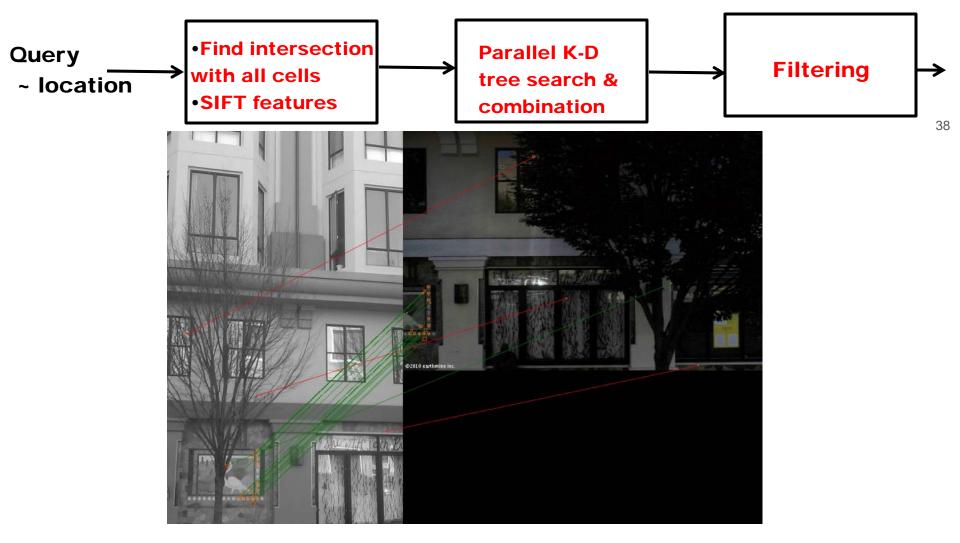


Example with ambiguity





Filtering to Improve Results

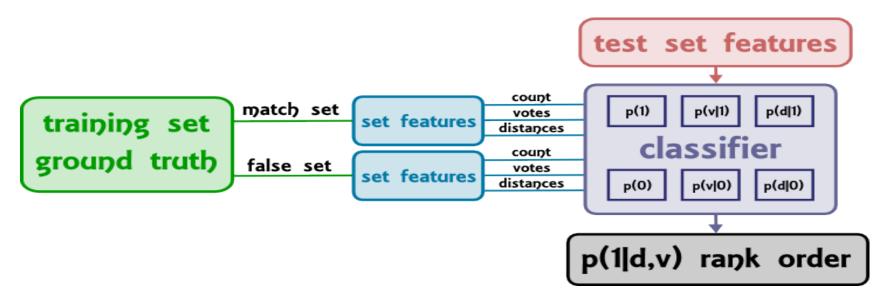


Filtering (1) : Geometric verification (GV) via RANSAC to eliminate erroneous feature matches Filtering (2): Compute the ratio between closest feature match & second closest feature match

Filtering (3): Machine Learning

C CALL

- Train a Naïve Bayes Classifier:
 - Training set: 65 query image ; each with on average 100 "candidate" matches;
 - Extract distance (d) from reported location & geometrically verified SIFT feature votes (v)
 - Generate the prior and conditional distributions p(m), p(d|m), and p(v|m); m = match;
- Test the classifier on new data by extracting votes & distance

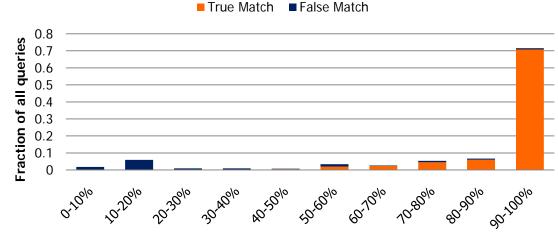


- Classifier predicts the *probability* p(m=1|d,v) that a candidate image is a match
 - Rank order dB image set
 - Confidence level in each dB image

Match Confidence is a good indicator of Match Performance



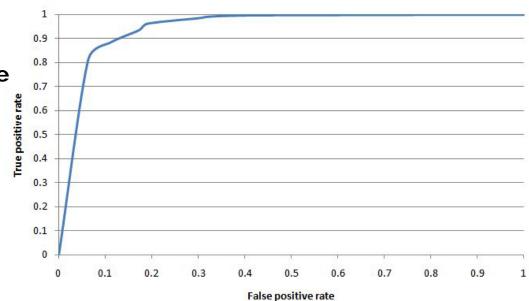
Match Performance vs Match Confidence



Match Confidence p(m=1|d,v)

Based on confidence of the best match, can ask the user to re-take the query image, if needed

Match Confidence Threshold ROC Curve



Earthmine Data Set: Panoramic Locations





Data Sources

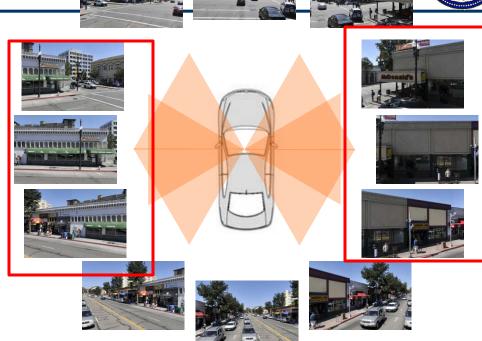
- Image Database:
 - ~ 2000, 360 degree panoramic images of downtown Berkeley
 - Processed into ~12000 geo-tagged 768x512 "street-view" images
 - One square kilometer
 - 25 cells of radius 236 m
 - ~ 1500 images per cell
 - **Query Set**

- Camera SLR Nikon camera D40x w/ 18-55mm lens:
 - Sets 1 and 2: wide angle
 - Set 3: varied focal length
 - Wide angle, zoom, normal
 - ~ 90 landscape images per set
- Cell phone camera
 - **HTC Droid Incredible**
 - 8 megapixel camera, autofocus, focal lengtň 4.92mm
 - ~ 110 portrait images per set
- Geo-tag images: GPS on cell phone:
 - +/- 10 meter accuracy \rightarrow too fine
 - Emulate errors of up to 100 to 200 meters



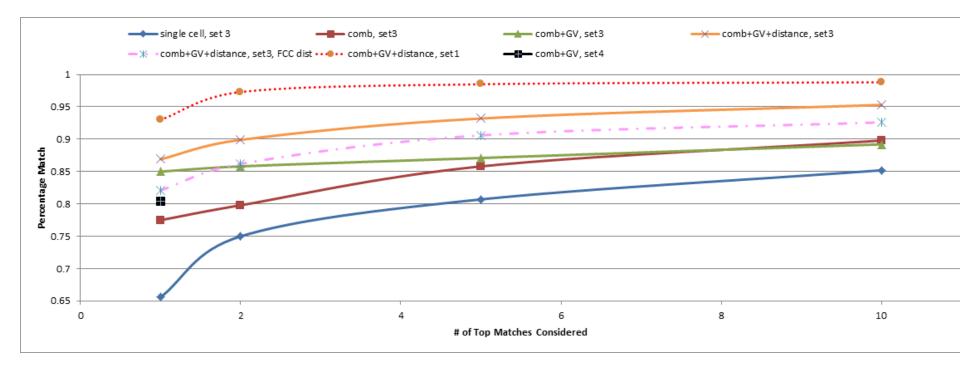


Digital Camera





Experimental Setup and Results



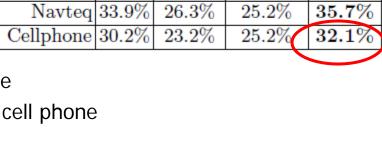
•Causes of Failure:

- Query pictures taken close-up often with shadows
- Heavily obscured by tree branches
- Not a correct pose match in the db
- Matched common objects

Comparisons with Existing Approaches

- Pollefeys et. al. 2010
 - Uses Earthmine database
 - San Francisco, not downtown berkeley
 - ~30000 images in database
 - Good performance if trained and tested on Earthmine
 - Much lower performance than our system for actual cell phone

- Girod et. al. 2008
 - Discretizes user location on-the-fly
 - $30m \times 30m$ cells/loxels $\rightarrow 20$ times smaller cell size
 - Assumes near perfect GPS localization
 - Generates kd-tree on the client from 9 loxels



83.0%

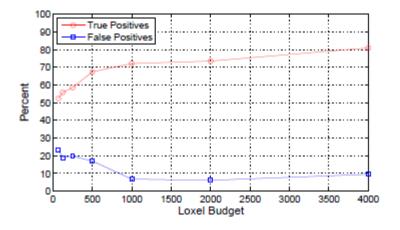
26.3%

Earthmine 84.3%

Affine Masked Rectified Upright

82.6%

25.2%

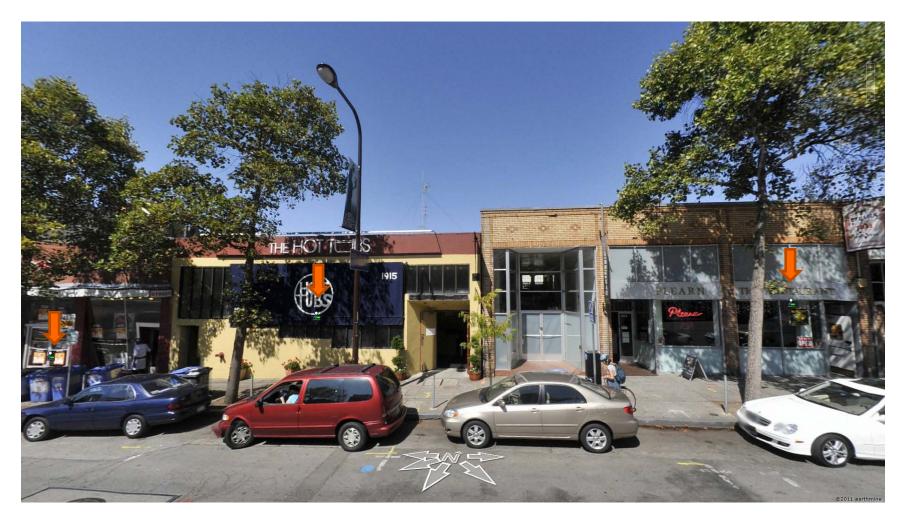




85.0%

Annotating Query Image





Earthmine Tagger: User tags panoramas

Tags are converted to 3D locations in space

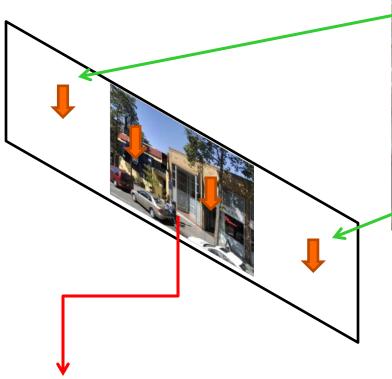




Project all tags in vicinity of database image onto database image plane



- •Use location/orientation info of image dB
- •Query image might have more Buildings/landmarks than dB image





dB image

Transfer Tags onto Query Image





Transfer Tags onto Query Image (2)







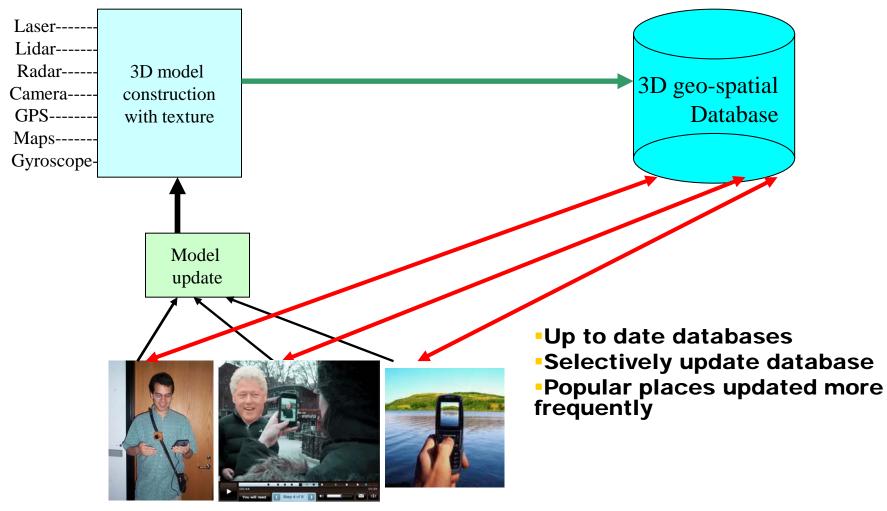
Future Technical Challenges



- Optimum division of the computation between cloud and client
 - Battery drainage considerations
 - CPU asymmetry between cloud and client
 - Communication cost between cloud and client
 - Cloud processing for one time image based localization
 - Takes 6 second on a server:
 - 2 seconds for finding SIFT features
 - 2 seconds to do k-D tree processing
 - 2 seconds for combining & filtering
 - Assumes compressed JPEG image sent to the cloud
- Tracking the user and updating the tags:
 - Real time; interactivity
 - Initial localization at cloud; update at the handheld

Model Update via User Generated Image/Video Content → crowdsourcing





Mobiles with cameras

Indoor AR applications

- Why indoors? Shopping centers, airports,
 - Holy grail of mobile advertising & location based services
- No GPS:
 - No easy way to come up with coarse localization for AR
 - Automatic 3D modeling of indoors is hard → research area





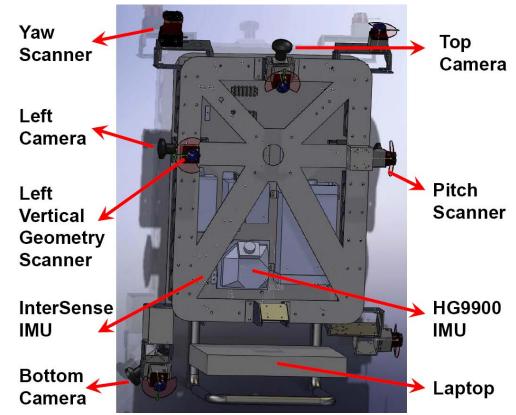




UC Berkeley: First in 3D Indoor Modeling

 Use a human backpack equipped with sensors to automatically generate 3D photorealistic textured models of indoor environments







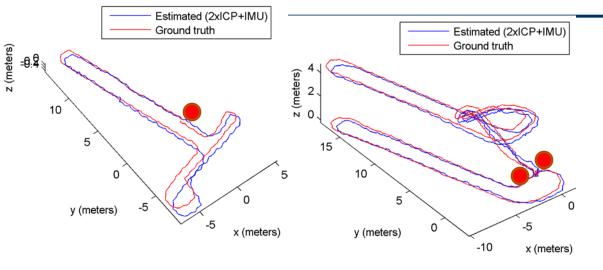
Examples





Key Step in 3D Model Construction: Loop Closure



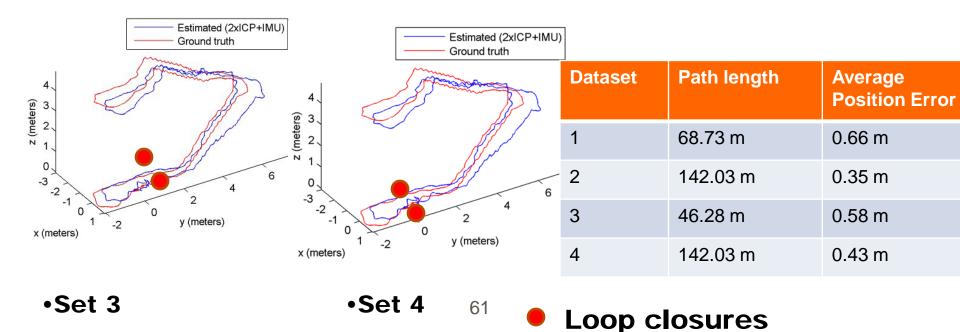


•Loop closure (LC):

- Revisiting same location
- Reduces error in
 - **3D model construction**
- Use Camera to detect LC automatically

•Set 1

•Set 2



Automatic Image Based Loop Closures (AIBLC)

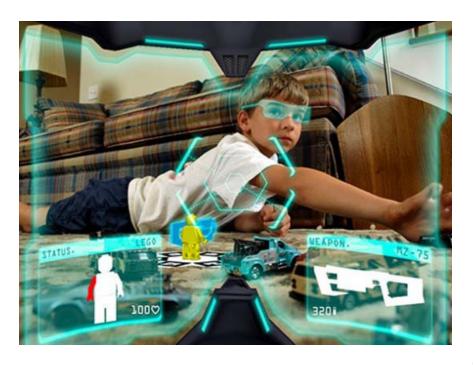


- Same approach for AIBLC for indoor modeling can be applied to indoor AR localization
 - OK not to have GPS or any other coarse indoor localization
- Details:
 - Fast Appearance Based Mapping (FAB-MAP):Cummins & Newman IJRR 2008
 - Generate rank ordered list of candidate image pairs
 - Prune the list via "key point matching"
- Upshot: Same basic approaches of outdoor AR localization can now be applied to indoors



Augmented Reality in 2020

- Almost certainly, many more AR apps on cell phones:
 - Mobile advertising
 - Location based service
- Most likely, 3D AR apps with compelling user experience:
 - Gaming and entertainment
- Ultimate goal: blur the line between real and virtual





Summary and Conclusions

Carlo Carlo

- AR no longer the technology of the future;
 - All key technological ingredients are available here today
 - Sensor equipped cell phones, fast networks, image recognition, user interface, databases, cheap CPU

 Only a matter of putting these together in the right way to truly enhance user experience