Collaborative Imaging of Urban Forest Dynamics: Augmenting Rephotography to Visualize Changes over Time

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ABSTRACT

The ecological sciences face the challenge of making measurements to detect subtle changes sometimes over large areas across varied temporal scales. The challenge is thus to measure patterns of slow, subtle change occurring along multiple spatial and temporal scales, and then to visualize those changes in a way that makes important variations visceral to the observer. Imaging plays an important role in ecological measurement but existing techniques often rely on approaches that are limited with respect to their spatial resolution, view angle, and/or temporal resolution. Furthermore, integrating imaging acquired through different modalities is often difficult, if not impossible.

This research envisions a community-based and participatory approach based around augmented rephotography of ecosystems. We show a case study for the purpose of monitoring the urban tree canopy. The goal is to explore, for a set of urban locations, the integration of ground level rephotography with available LiDAR data, and to create a dynamic view of the urban forest, and its changes across various spatial and temporal scales. This case study gives the opportunity to explore various augments to improve the ground level image capture process, protocols to support 3D inference from the contributed photography, and both in-situ and web based visualizations of the temporal change over time.

Keywords: mobile rephotography, imaging, urban ecology, LiDAR, Bundler, PMVS.

1. INTRODUCTION

Cities throughout the world are increasingly looking for green solution to tackle issues as diverse as reducing the urban heat island effect to increasing property values. Urban tree canopy goals have been one of the most visible of these green solutions. As cities set these goals there is a need for new ways of monitoring the status of urban forests and capturing a collective and dynamic record of change are required. This problem domain is an exemplar of measurement scenarios where there is a need for measuring trends over broad areas, but for which traditional forms of measurement (e.g. overhead imaging) have various shortcoming. We explore how the very simple concept of rephotography may address this need by supporting public participation in large scale data collection[1-3].

Rephotography is the process of taking a picture of the same scene, from the same viewpoint. This serves to highlight changes in the scene, rather than changes in the composition. Figure 1 (right) shows an example rephotograph showing changes in a street tree's leaves and the addition of a gator bag (used to regulate water) in the tree box.

Figure 1: Sample images using the RePhoto smartphone app (from *projectrephoto.com*), showing images of the same urban street tree, as photographed 24 January 2012 and 7 August 2012. The RePhoto app includes overlay tools that augment live camera views to facilitate alignment of successive pictures, which is key to simplifying subsequent image analysis.

We propose an approach to rephotography that uses a variety of augments to help calibrate contributed imagery and to visualize the changes in an area over time. These rephotography augments are integrated within a smartphone mobile app. In this paper we highlight the potential to integrate resulting ground level imagery within the context of large scale aerial LiDAR and images captured at different times.

This infrastructure addresses a general challenge common to many image or data acquisition tasks; that data is often captured at various spatial resolutions and different time scales. In the context of urban forestry, overhead imaging techniques such as satellite and aerial imagery, and airborne LiDAR, can yield data that are spatially complete yet temporally sparse (currently on the scale of 5 to 10 year intervals)[4]. Furthermore overhead imaging modalities have a singular perspective, straight down, and are thus unable to resolve key features, such as the trunks of trees. Ground-based imaging, such as mobile LiDAR, are only in their infancy and not commonly available. Explicit inventory surveys are costly because they require trained crews, often with specialized equipment (e.g. the UFORE methods outlined by Nowak and Crane[5]). Thus, much like the overhead surveys, such inventories are only carried out at 5 to 10 year intervals. An alternative point in the data capture spectrum are sets of fixed persistent camera images, such as the Phenocam project[6], which use webcams to provide continuous monitoring, capturing images every hour over a period of years, but from a limited set of locations.

Mobile imaging and rephotography resides at an intermediate point between the spatial completeness of LiDAR and continuous capture frequency of web cams. Our contributions are: (1) a freely available smart-phone app that offers photographic overlays (rephotography augments) to enable a person to photograph a location with the correct perspective and geometric relationships to match a prior image, even if the images are taken years apart by different people, (2) a corresponding database of locations and imagery that keeps track of where images are needed at a given time, and (3) a proof of concept demonstration of how these images can be post-processed to extract information or integrate with other data sources.

As a potential use case, we explore the domain of urban forest monitoring. We explore ground level imaging of many individual trees collected by individuals that live in the area on an ongoing basis to create dynamic views of the urban forest. Within the development of the smartphone app, we explore the potential of overlay augmentations within the picture taking process for guiding individuals to ensure consistency in measurements over growing seasons. We explore data capture protocols that include slight variations in the viewpoint so that multiple 2D images of a scene can be merged to create a 3D model. Even with careful data capture protocols, these models have several drawbacks – a scale ambiguity, and challenges in measuring the complicated microstructures of a tree canopy. Thus we also explore how to integrate ground level imagery with airborne LiDAR data which captures the tree canopy well, and has an accurate global scale, but which does not see the ground level tree structure.

Collectively, these approaches explore capturing individual tree dynamics in the context of local ecological changes, in a way that is not possible from LiDAR or any other single imaging modality alone, and in a way that reflects the importance of people and the overall social context to the dynamics of urban ecology.

2. SYSTEM DESIGN

Participatory rephotography has three main components. A mobile app supports capture of aligned pictures in locations of interest. A database keeps track of rephotography subjects, and highlights locations where additional images are needed. Finally, the database backend supports a variety of visualization/data-processing tools that merge images taken of each subject. To explore this system design, we first offer a pipeline that we have used to support urban tree monitoring. As we describe each component, we also explore potential modifications to the framework that support alternate uses.

2.1 Mobile Rephotography App

The rephotography mobile app is shown briefly in Figure 2. It shows a map in the neighborhood of the user, querying a database to find and display all the photographic subjects near the user (shown as green pins, in the screen capture marked “1”). When the user selects a pin, the initial view (photograph) of that subject is shown to the user to validate that they are at the correct place (2), then an image capture mode opens where a previous picture is shown as an augment to the live camera view in a number of possible ways to allow the user to align the new view accurately with the previous image (3). When captured, the new image is uploaded to a database.

Figure 2: Workflow of the rePhoto app, (1) choosing, then (2) verifying the photograph subject, then (3) aligning the current camera view to match the previous picture, and (4) uploading the image.

Opportunities to use this system in different ways arise from choices of (a) what images are used for image alignments, and (b) choices of the frequency or timing at which images are captured. While we have, to date, used an initial image of the subject as the image for later alignment, one can use cartoon images to support alignment of different individual subjects, edge maps to support better alignment, etc.

2.2 Rephotography Database

This basic system design can support projects at different spatial and temporal scales. Active projects that relate to tree growth include multiple neighborhoods in NYC that we discuss in greater detail in section 3, a test case observing many different types of scenes near Washington University with a focus on LIDAR integration, and rephotography locations at most scenic overlooks in the US highway system.

Figure 3: Screen captures of rePhoto subject maps for continental scale projects (left) and high-density urban projects (right).

At startup, the smartphone app queries a database to find nearby subject locations. Each location includes a tag of whether an image is currently needed (pin colored green, as shown in Figure 3) or not (colored red), although nothing prevents a user from contributing pictures that are not needed. Images are uploaded to the database after they are captured, and the database can evaluate if additional pictures are needed of that subject. Simple rules to evaluate include: (1) the greedy approach of always requesting additional images, (2) the minimalist census model of requiring just one picture of each subject, (3) a time-lapse supporting model requiring pictures if no picture has been taken within some time period. More complicated rules require processing of the image content itself as discussed next.

2.3 Data processing pipeline

Our current system runs on the database server and analyzes the set of images of a particular subject each time a new image is uploaded. This processing could include improved alignment to make more accurately aligned images. To date, however, we have spent more effort in exploiting the fact that images are not taken from exactly the same location to explore the ability to infer 3D models of the subjects. This is done with the Bundler/PMVS package, where Bundler[7] finds corresponding points in the set of images and uses bundle adjustment to solve for the camera locations, rotations, and focal-lengths, and PMVS – Patch Based Multi-View Stereo[8] , uses that camera geometry and image patches to solve for a dense 3D model of the scene.

This 3D model has a scale ambiguity (if the scene was half the size, and the cameras where half as far apart, the images would look identical). We have not, to date, found a compelling approach to solving this ambiguity in the mobile data capture domain; the GPS locations are not accurate (at the scale of taking pictures around a tree), most smart phones do not share the “focus distance”, and there is sufficient variability in the heights of picture takers to preclude the use of a default human height as an effective ruler. For the purpose of urban tree monitoring, we detail in section 3.2 below how we attempt to use co-located LiDAR data to give a scale to the model, but also believe that this is an important problem to continue to explore.

3. USE CASE

3.1 Community imaging of urban trees:

In the summer of 2012 we conducted a field trial of the mobile rephotography app for an urban tree monitoring use case. Our team worked with the New York City Urban Field Station (a collaborative partnership between the NYC Parks & Recreation and the US Forest Service) to capture data in Queens and with TreeKit, a nonprofit tree inventory group, to capture data in Brooklyn and Queens. Digital tools and methods overcome a common limiting factor of volunteer-based data collections: paper-based methods are quick in the field but have lag-times between data capture and input to digital databases, thereby decreasing the adaptive potential of the data. Thus facilitating persistent and ubiquitous monitoring of individual trees via mobile rephotography can dovetail with stewardship of urban forests and support the work of volunteers.

Figure 4: TreeKit volunteer survey group.

For this use case/field trial, community volunteers from the Gowanus Canal Conservancy participated with us utilizing paper-based protocols alongside our mobile tools (Figure 5, left). Areas of NYC with representative tree pit density and tree species variation were selected in consultation with our community partners. Volunteers utilized TreeKIT mapping protocols and paper worksheets to plan routes and document tree locations (Figure 5, right).

Figure 5: Planning tree survey routes in the Gowanus Canal area for field research using the mobile application alongside TreeKit paper-based mapping protocols.

Three types of data were collected for trees during the field trial: location, diameter at breast height (DBH) and primary imaging and rephotography. Location information was captured utilizing a walking tape measure to measure distance from street corners and the resulting geometry and distances utilized to calculate a unique geo-hash code for each tree pit. DBH, is a standard metric utilized to monitor the growth/health of trees (Figure 6). Either a standard or specialized tape measure is used to collect this measurement.

Figure 6 : Collecting ground-based data for individual trees in New York City

This census and measurement procedure seems ripe for potential automation, and both initial imagery and rephotography were captured utilizing the RePhoto application. To populate our subject database we initially hoped to use available urban tree census data to identify tree locations. However, these often index trees by approximate street address, and this is often insufficient to disambiguate street trees, when several are nearby, or in urban areas with unusual street numbering protocols. Thus, we use existing LiDAR data and state of the art approaches to finding trees from LiDAR tree canopies[9,10]. The tree locations in the right panel of Figure 4 (above) were computed in this way to provide locations for data capture for the NYC community use case/field trial.

To support quantitative measurements of tree canopy size, multiple perspective views were captured to facilitate 3D point cloud generation for select trees. Figure 7 shows example images of one select tree, in Fort Totten, NYC, and the result of using these images in state of the art 3D reconstruction software. However, the 3D point clouds generated in this way are not geo-registered and have an uncertain overall scale, which led us to explore integration between these Bundler models and well calibrated LiDAR data.

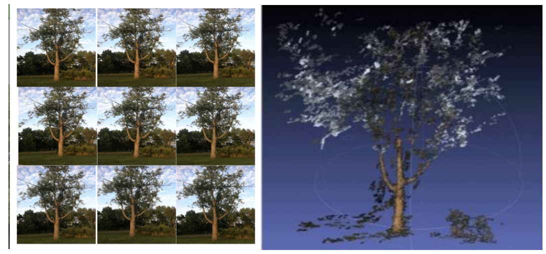

Figure 7: Left, nine of a series of 21 images of a tree at Fort Totten, NYC, that were then utilized to generate the 3D point cloud/model of this tree on the right.

3.2 Bundler / LiDAR integration

Relating data from ground level imaging to overhead imaging has dual purposes; first, ground data can complement periodic aerial imaging studies with higher frequency volunteer data acquisition. Second, the LiDAR data of a region is well calibrated and can accurately place and scale products created from ground level data. The LiDAR for New York City was acquired by an airborne sensor in the spring of 2010 with an average point density of 8-12 points per square meter. The data have a 33.08 cm horizontal accuracy and 7.48 cm vertical resolution. The top inset in the left panel of Figure 8 shows LiDAR data for the same tree in Fort Totten (as shown in Figure 7), demon-strating that while there is adequate data for the tree canopy, there is absence of ground level information for the tree trunk. The inset below it juxtaposes the 3D point cloud/model of this tree, in the context of the LiDAR. The panel on the right shows the merged LiDAR and point cloud data as a proof-of-concept for one way in which ground-based imaging can complement aerial data collection.

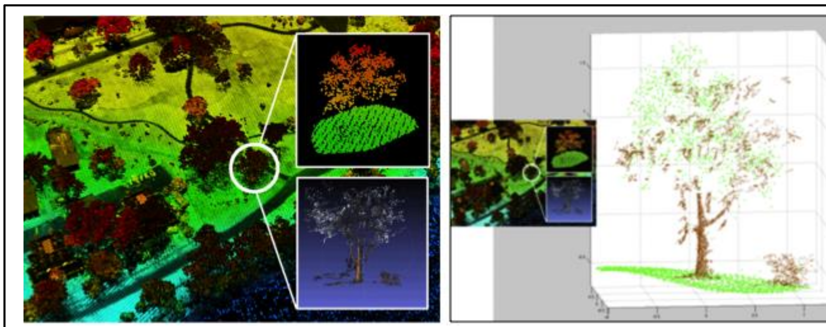

Figure 8: Inset on left is overhead LiDAR of an individual tree and the 3D model of that same tree created from 2D mobile phone imaging and rephotography. Right panel is a 3D model of the tree created by merging the overhead LiDAR tree canopy data (green) with the 3D model of the tree trunk and limbs created from ground-based 2D image data captured with the cell phone application (brown). Tree is centered at Latitude 40.794691238, Longitude -73.777994529.

Both Bundler/PMVS and LiDAR give 3D point clouds, but they reside in different coordinate systems, and the Bundler/PMVS model has an unknown scale factor. Thus, aligning 3D models from Bundler and LiDAR requires solving for the 3D translation, rotation and scale needed to match the coordinate systems. This is challenging to automate because the 3D point clouds from LiDAR are primarily in the tree canopy, and the parts of the tree that are stable enough for Bundler to match are primarily on the tree trunk. To date we have explored a user-in-the-loop method that requires the user only input the coordinates of three corresponding points, providing 9 constraints (sufficient to solve for the 7 unknowns).

However, it is difficult for even practiced users to find, by hand, corresponding points. We have had most success with a few additional assumptions.

First, we assume a flat ground plane. LiDAR point clouds are commonly given in a coordinate system where the Z-axis is perpendicular to the ground plane, and we translate the points along the Z-axis so that the lowest point is assigned to be at zero. Second, as our protocol asks one to walk around the tree and take pictures, we assume that all camera locations were the same height off the ground. From the 3D bundler model (which includes the camera position), we solve for the best fit plane containing those camera positions, and then solve for the rotation so that plane is parallel to the ground plane. By fixing both ground planes, we remove one translational degree of freedom, and two rotational degrees of freedom. To solve for the remaining translation (sliding along the ground plane), rotation (around the Z-axis) and the relative scale, we ask a user to find two corresponding points. We use Nelder-Mead optimization to minimize the sum of the squared errors between each correspondence. This optimization is very fast, allowing a user to judge the visualization of the resulting overlapping point clouds. If the alignment does not look plausible, the user can adjust or choose new correspondences, and usually just a few iterations are needed. An additional example of the alignment of Bundler 3D point clouds (in gray-scale) and LiDAR data (colored dots) is shown in Figure 9.

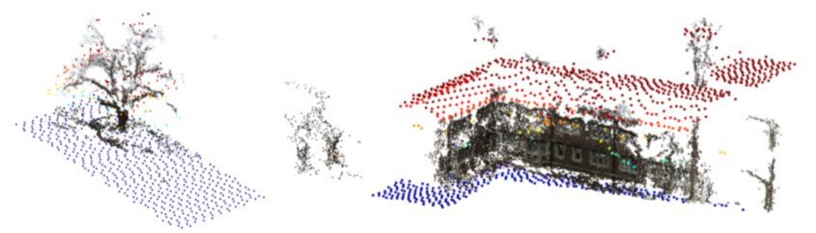

Figure 9: Inset on left is overhead LiDAR of an individual tree and the 3D model of that same tree created from 2D mobile phone imaging and rephotography. Right panel is a 3D model of the tree created by merging the overhead LiDAR tree canopy data (green) with the 3D model of the tree trunk and limbs created from ground-based 2D image data captured with the cell phone application (brown).

The Bundler model is much higher resolution, though often incomplete in image regions without good features to align. Aligning to geo-referenced LiDAR points fixes the scale, position and orientation of the bundler model. In figure 9, the scene includes a tree in front of the corner of a building; the entire scene was registered at one time, but was manually separated to make the resulting 3D model easier to show in a static picture.

4. REFLECTIONS AND FUTURE WORK

4.1 Future work

We are excited about building tools to support public participation in data collection, especially in the ability to capture data that provides quantitative measures that are difficult or impossible to obtain otherwise. Engaging the public in building models of the urban forest, and subsequently building visualizations of its health and change over time, supports eventual self-sustaining engagement. Additional work is necessary to explore data capture protocols, to make alignment, model building, and biological health assessment easier and more accurate.

Additionally, the amount and variety of global data sources is vital to solving various problems in participatory data collection. In our simple use case, the rePhoto app employs a convergence of advanced object recognition algorithms on LiDAR data to populate an initial database of photographic tree subject locations, shows those as pins to the user referenced to google map data, solves for a 3D model using Bundler on a set of images, and then fixes the scale of these images by subsequent alignment of features to LiDAR. The potential applications of mobile participatory data collection will grow as it becomes feasible to integrate additional or alternative data sources in the user interface, data alignment, or data analysis stage

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