Analyzing, Preparing, and Processing Input Geospatial Data for High-Resolution Terrain Generation

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ABSTRACT

Automatic generation of high-quality terrain data for use in military training applications (especially, integrated Live-Virtual Training) depends heavily on gathering and acquiring high-quality and high-resolution data from a variety of appropriate sources. One of the more accessible sources today comes from images collected by drones. Using photogrammetry, the images are often post-processed to produce detailed 3D representations of the environment. Starting the data generation process with clean data substantially reduces the need to remove anomalies or to perform unnecessary processing further in the terrain database generation pipeline. Unfortunately, quality data is not always provided or available. High resolution collection sources often produce outputs that include inaccuracies, errors, or suboptimal content. The increase in resolution also adds to the challenges in discerning between accurate and erroneous aspects of data. Recent collections also highlight the need for more sophisticated geometric analysis methods and tools to detect and remove anomalies that are geometrically joined with, or close to, good data. Therefore, the input data must be further analyzed, cleaned/corrected, and prepared to make it usable in the terrain generation process. This paper describes some of the key techniques and the analysis process used to (a) improve the collection process and ensure data collection approaches yield the highest quality data possible, (b) leverage AI/ML techniques to detect, then fix (or at least reduce) anomalies in suboptimal input/collected data before the data is further propagated through the pipeline, and (c) combine both AI/ML and algorithmic automation to extract the desired content needed in generating high-resolution terrain data.

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Tu Lam is a Senior Software Engineer at Leidos where he develops tools and processes to generate 3D terrains using photogrammetry, turning photographs into 3D data. He has 25 years of experience in 3D technologies including patents for 3D character animation innovations and medical training simulations. He also develops mobile healthcare apps which have been downloaded 2+ million times and holds a Bachelor of Science in Computer Engineering from the University of Florida.

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INTRODUCTION

Accuracy, precision, and resolution of data are important factors in many computing applications that model or simulate the real-world environment. These factors become especially critical when integrating the models and simulations with Live training activities. Models of the environment, particularly terrain-related data, must include sufficient resolution and accuracy to support correct results in such computations as inter-visibility and munition effects, while avoiding negative cues to the trainees. This means the model or the simulation must contain enough information to represent the real world with sufficient fidelity, where it counts, and when it counts. Although the notion of "sufficient fidelity" can be subjective and also depend on the specific training application and/or objective, it can be tempered and bound by how the results of a computation invokes and matches the required training reactions. In support of these modeling and computational goals, rigor must be applied in the collection and the subsequent processing and generation of high-quality, and sufficiently high-resolution, terrain-related data.

Generation of high-quality and high-resolution terrain data involves several challenges. Some of these challenges are associated with the physical collection and subsequent analysis of source data, and some are related to processing, managing, and tailoring the content. In some applications, the inclusion of high-resolution data means the required resolution can be fabricated, providing the required detail. Although this approach works for applications in which geo-typical (not geo-specific) data is sufficient, it does not work when Live training is involved. In addition, the terrain data generation pipeline is (or should be) agnostic to data resolution. This allows mixing and matching the right (resolution) data for the applications at the required level. Independent of data resolution, at a broad data generation overview level, the work can be partitioned into three bins, as depicted in Figure 1.

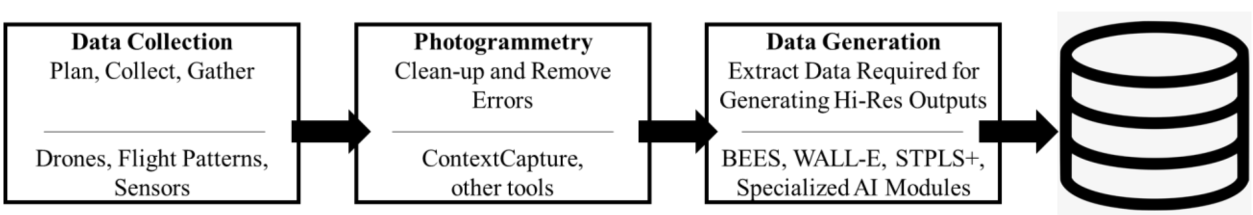

Figure 1 – Process Overview

In practice, even the best source data requires evaluation, analysis, and often clean up. In cases where data that is more current is required, previously collected source data may not be sufficient. For unrestricted sites that can be accessed relatively easily, use of new photographs or LiDAR data is often desirable since the cost of collecting such data by using drones and other instruments has become affordable. Such collected source data can be used in combination with more traditional sources such as existing digital terrain data products, satellite and aerial data, and maps. However, whether existing or new, the act of combining data usually requires analysis, cleaning, normalizing, and adjudication of the data across relevant sources. In short, existing or newly gathered source data is almost never clean or useful as-is.

Anomaly removal is often a significant part of data clean up; otherwise, the final data products are as good (or as bad) as the starting data. It is important to note that what can be considered an anomaly in a given context is not always an anomaly or noise. For example, in and of themselves the presence of cars, trees, or clouds in overhead imagery are not anomalies, unless the goal is to identify and determine the terrain surface positions. Therefore, automating the identification and removal of noise/anomaly artifacts, and in general automating data clean up, is a non-trivial task, requiring clear criteria and more intelligent analysis. After preparing the input source data, finding and extracting the desired data remains a challenge. Furthermore, automating object identification and extraction presents yet another layer of challenges.

Within this context, this paper focuses on exploring methods for improving the collection approach to yield better content, leveraging automated techniques to detect and fix (or at least reduce) anomalies in suboptimal collected data, and using automation to extract the desired content.

TECHNIQUES FOR AUTOMATED DATA COLLECTION

To build accurate higher resolution training environments, the use of drone-based photos or LiDAR can provide richer and more current content than traditional sources (such as satellite data). However, even with increased resolution, addressing inaccurate or erroneous aspects of the data remains a challenge. Errors due to insufficient coverage of an area can sometimes be subtle and difficult to detect by humans. These types of errors can also vary greatly in size and shape which can make them resistant to automated methods. Anomalies that are spatially close to, or joined with, good geometric data are particularly challenging. Even using new collections of the same area can introduce new types and locations of error, often reducing the benefits of any error removal steps taken with previous collections. To address these types of problems, the data collection process needs to: establish context-specific or application-specific goals; identify and understand collection challenges and pitfalls; and develop and use techniques to improve the collection parameters and process. It is important to note that the challenges, the solution approaches, and the preparation for data collection are not unique to the modeling, simulation, and training application domain, since these can equally apply under other contexts, including military operations.

Data Collection Goals

The goals of data collection are to increase the accuracy of the collected source data and the efficiency of the collection process. Since collected data is used at specific stages of the terrain database production pipeline, it is also a goal to properly reflect the requirements of those stages in the data collection process. In some cases, the collection process must be tailored to specific goals of a data production activity, which in turn can be tied to specific application goals and objectives. For example, content and fidelity of data can vary significantly based on whether the data will only be used in the Virtual domain or also in the Live domain. Therefore, the requirements for source data, and correspondingly the requirements and parameters of the collection process, will also depend on these goals. Additional work is often needed to determine whether all goals can be met with a single collection process, or for each case a specific plan is required that answers: what data is needed; for what database generation purpose; and how that data must be captured. Such a plan often includes a checklist based on the parameters that drive the specific production objectives.

Improving Data Collection

It is desirable to automatically create collection plans and checklists, based on a set of criteria and input parameters. However, this can only be done after enough manual approaches have been tested and used (Leidos, 2022). Whether collection plans and checklists are created automatically or manually, identifying a proper mix of collection capabilities is a first step and includes answering such questions as:

- Can multiple sensor payloads be used on the same platform at the same time?
- How much overlap of the subject from different positions/angles is needed, under what conditions/configurations?
- Can different sensor bands (for example, visible or near, mid, and far infrared (IR)) be supported and affordable?
- Can payloads include emitters to illuminate the scene that the sensor can then capture?

While establishing the collection goals and the engineering processes, the following topics need to be addressed:

- Developing and defining data collection guidelines and methods based on the collection subject, access to it, and the type of collection.
- Types of sensors to be used and their suitability for the collection objectives.

- Urban settings vs. open fields.
- Interiors and exteriors of structures.
- Season and time of day considerations (e.g., lighting, shadows).
- Access to, and adjustment of, sensor parameters.
- Ability and feasibility of concurrent data captures with multiple sensors.
- Use of the appropriate platform (drone, ground vehicle, human, etc.) for the collection.
- Control of the platform's path.
- Automatic path adjustments during collection.
- Validating the positional accuracy of sensor (and the platform).
- Accurate recording of the conditions for each instance (snapshot) of a collection, such as: time and absolute reference position; sensor angles/orientations, and relative positions; and sensor parameter settings (e.g., sensor size, focal length, aperture, shutter speed).
- Identification of the stages and points in the data production pipeline where all or some subset of the collected data would be leveraged.

Before a collection, the following should be predetermined:

- Extent of area of interest (including the buffer zone)
- Collection equipment:
    - Sensor (e.g., electro-optical/LiDAR/thermal)
    - Platform (e.g., drone/tripod)
    - Surveying tools (e.g., total station, theodolite)
    - Ground control point targets
    - Lights for interior building collections

Insights on Good Collection vs. Less-than-Optimal Collection

Data collection within interiors of structures and buildings involves its own set of good vs. poor practices (Katzman & Moran, 2023). Although the scope of the research includes both exterior and interior collections, this paper focuses on collections associated with exteriors of buildings and open fields. Preflight planning is an important part of successful exterior collections, and its goal is to increase accuracy and improve efficiency of the collection process. The data generation goals can differ based on end-use target applications; however, there are key techniques in the collection process that can apply commonly across projects and will result in higher quality data generation.

Consistency and accuracy in the data collection process are critical to the cross-correlation of collected data and their real-world counterparts. When possible, positioning and camera direction need to stay consistent throughout the collection process such that tie-points can be determined from the collected images (Bentley, 2023). These tie-points are used in both algorithmic-based and neural network-based approaches for photogrammetric detection. This is why it is important to have significant (recommended 70%) overlap between images. This maximizes the chances of algorithms detecting and matching objects across multiple images. Experience has shown that less overlap between images leads to lower quality terrain generation, while higher percentage of overlap leads to better results.

50% Overlap 75% Overlap

Figure 2 illustrates the differences between two separate collections of the Ujen MOUT site. The green dots signify the number of usable photographs, while the red dots signify unusable photographs. More images were usable in the 75% overlap collection because the higher overlap of images allowed photogrammetry detection to match more tie-points.

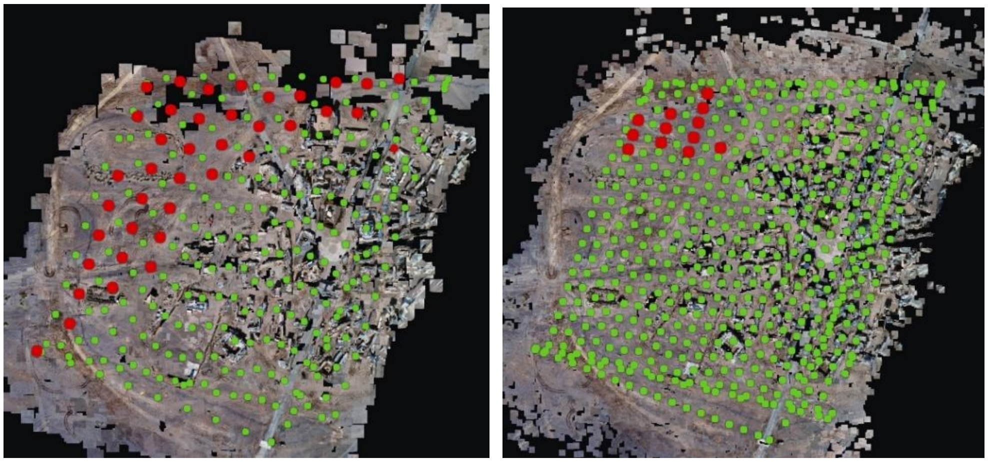

Figure 2 – Differences Between Drone Collection Overlaps – Ft. Irwin, Ujen MOUT Site

Data collection is often a time-intensive process, and usually the time requirement is directly tied to the size of the collection area. Therefore, it is important to define and establish a collection plan in advance of the collection event. Targeting a required overlap and defining a collection area allows for a more rigid collection approach. The desired number of photographs can be determined using the area, target overlap, and camera field of view settings. The formula to calculate spatial ground resolution for a photograph in meters per pixel is as follows (Bentley, 2023):

$$R = \frac{S \times D}{f \times L}, \text{where}$$

R is desired image resolution (m/pixel)
S is the greater size of the sensor (mm)
D is the distance between the camera and subject (m)
f is the focal length of the camera lens (mm)
L is the greater dimension of the photograph (pixel)

This formula can be used to help determine allowable camera distances from the subject matter, and subsequently allowable spacing between images. Planning routes within the collection site are especially useful in high density areas, such as buildings in urban settings or firing positions in complex terrain regions. Drone flight patterns, such as 'Lawn Mower' and 'Cross Hatch', are commonly used for collecting the full extent of a site (see Figure 3). The methods are compared using the same drone and camera angle. 'Lawn Mower' is the collection method of flying back and forth over the site taking pictures from one angle. This technique can be improved by flying the same path in the opposite direction to increase the number of photos from different views.

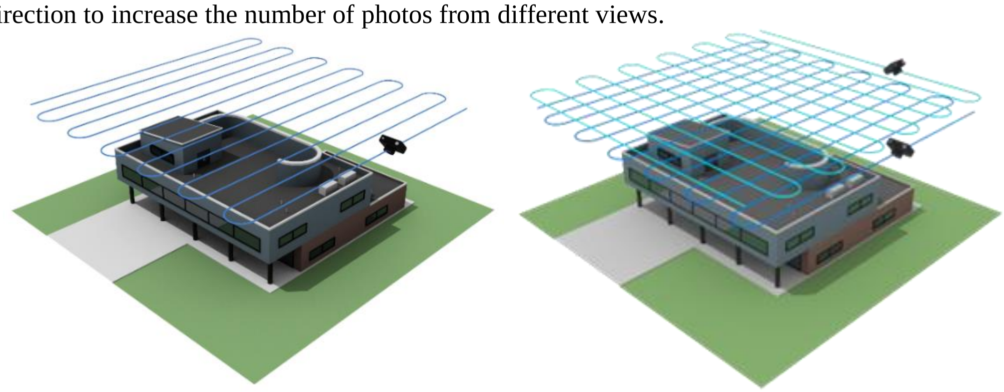

Figure 3 – Drone Flight Paths: Lawn Mower (Left) and Cross Hatch (Right)

However, the 'Lawn Mower' method does not provide enough information to reconstruct all sides of objects at a site because there are not enough views of the objects being captured. 'Cross Hatch' improves on the 'Lawn Mower' technique by crossing perpendicular to the original 'Lawn Mower' path. This is preferred, since it increases the number of views of the objects, allowing a higher chance of tie-points to be created between images.

Collecting data for specific objects of interest (e.g., a building significant to training) requires closer views and more angular coverage of the feature in order to capture content to an acceptable level of detail and accuracy. One method designed for these cases requires a drone to fly a radial path focusing on the subject. In order to have different views of the subject, multiple heights are required, as depicted in Figure 4.

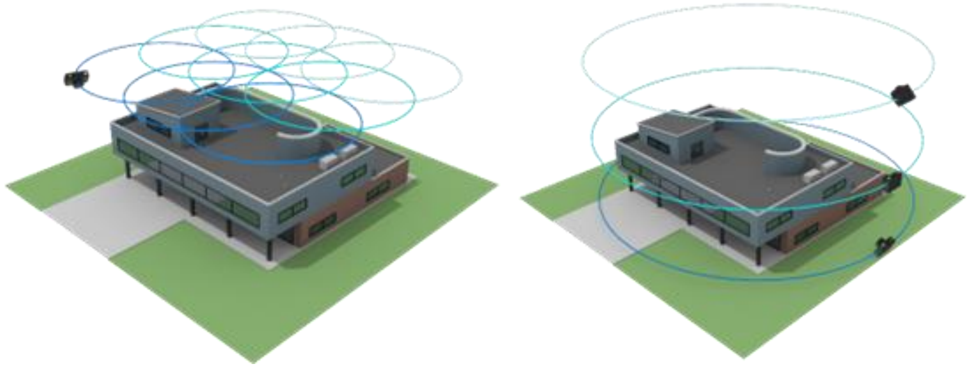

Figure 4 – Overlapping Orbits Drone Flight Paths with Multiple Heights

Another drone flight pattern designed for point of interest objects is adaptive 3D scan, in which the drone is programmed to move parallel to walls, look up and down to get coverage of the roof/ceiling and ground/floor, and go through or under openings (e.g., tunnels, patios). The advantage of this method is that a very high-resolution mesh and texture can be reconstructed using photogrammetry techniques. The disadvantage is that it can be very slow to cover a large area. An example of the adaptive 3D scan method is shown in Figure 5.

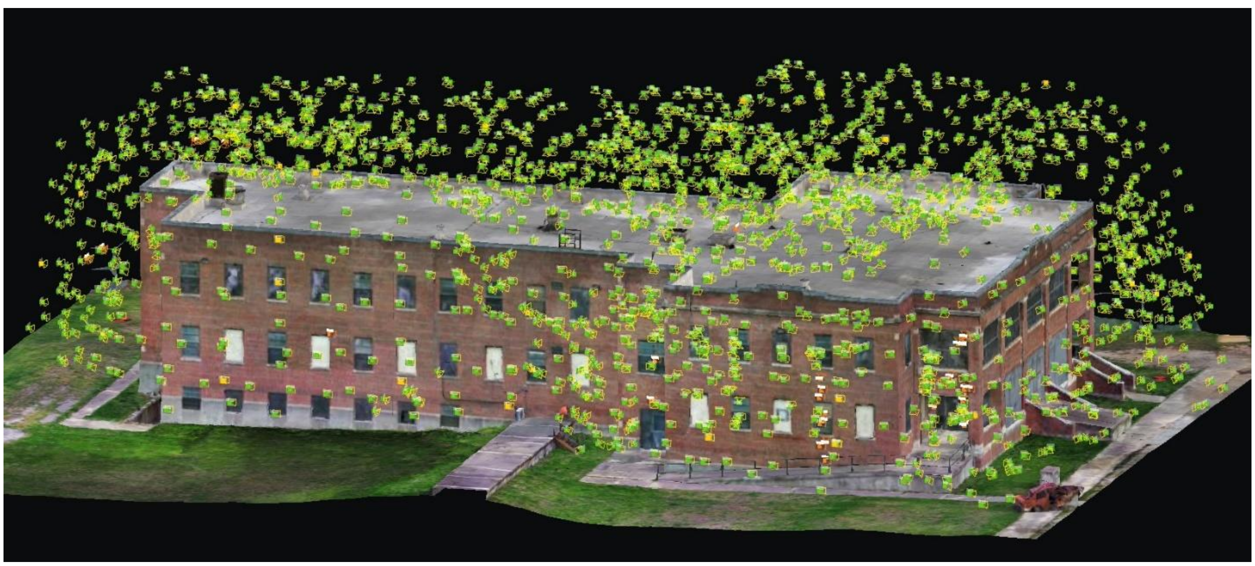

Figure 5 – Autonomous 3D Scan Drone Flight Pattern

Accurate position and orientation of platforms and their sensors are required for detecting and extracting 3D objects from 2D images. Algorithmic and artificial intelligence / machine learning (AI/ML) approaches rely on triangulating objects in 3D space by utilizing a platform's position in relation to the subject. For drone-based data collections, position and orientation can be incorrect due to unanticipated sources of error, including vibration and wind. Use of real-time kinematics (RTK) and post-processed kinematics (PPK) methods allow for position corrections either in real-time or during post-processing of data. Use of RTK vs. PPK depends on conditions under which collections occur. RTK is a better choice when conditions allow corrections to be performed at the time the data is being collected. Often, poor connections can occur between the RTK moving receivers and the base station. For example, signals can be obstructed by objects, or orientation of receiver antenna can change as the drone turns. Under these types of conditions, use of PPK is better suited.

The PPK method relies only on the Global Positioning System (GPS) signal data, which is then post-processed by using the collected positional data and correcting it relative to a reliable stationary receiver's position data (possibly much farther away from the drone) for the same time. Where possible, incorporation and use of Ground Control Points (GCP) will improve geo-referencing accuracy and will reduce geometric distortions over longer distances. GCPs are used to register known 3D coordinates with points on 2D photographs. The 3D coordinates are often obtained through traditional surveying methods (when possible) and each GCP's position must be identified in two or more photographs. Depending on the extents of the area, a minimum of three GCPs should be used, with more GCPs required when collecting over large areas. For photo-based data collections, an optimal physical spacing between GCPs is such that they appear at roughly 20,000-pixel intervals across captured images. For example, for a 2 cm/pixel photograph, GCPs should be 400 meters apart (Bentley, 2023). Use of inertial measurement units (IMU) with the platform/sensor greatly increases the accuracy of the position, velocity, and orientation of the captured data.

In photo-based data collections, the more detail there is in an image, the more accurate the resulting 3D models will be. Detail can be improved by increasing the pixel resolution of each image. Higher pixel resolution means more pixels dedicated for resolving the terrain and supporting greater accuracy in measuring features. Obtaining more terrain resolution with the same camera comes at the cost of more images that are needed to achieve the required image overlap. Since resolution is dependent on the distance from the object and camera settings, it is important to determine the desired resolution before collection. Camera settings are often fixed before a collection, making it important to set a target distance to determine the number of images required to achieve both resolution and image overlap (Bentley, 2023).

When possible, collection should be planned for optimal (or desired) time of day and year. Depending on sensors being used, considerations must include optimal time-of-day range, weather effects, and subject lighting/illumination. Strategic choice of time of day (e.g., dawn vs. mid-day) can be beneficial for shadow reduction and other artifact avoidance.

Often the edges of the collection area lack the required image overlap necessary to generate quality 3D content. This creates a bleeding effect where the edges of the area are lower quality than subareas inside the collection area. This is because not enough images are captured outside (or near the border) of the collection area to properly generate sufficient overlap of the boundary. Therefore, a buffer should be planned around the collection area to acquire additional data. Figure 6 illustrates an example of a buffer zone.

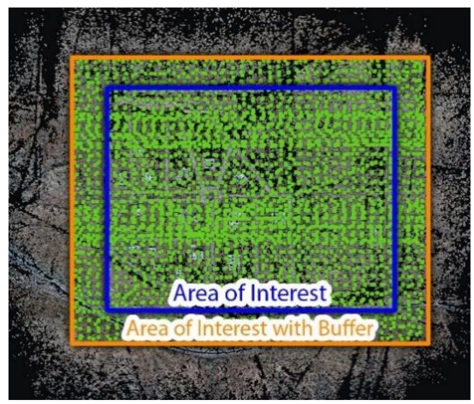

Figure 6 – Area of Interest with Buffer Zone

IMPROVING THE COLLECTED DATA

Once collected data has been analyzed and organized, it often requires some degree of clean up and correction. Producing high quality end-use data products is substantially easier when clean data is used to feed the data generation pipeline. Lack of clean data makes it difficult to separate terrain surfaces from nearby/surrounding features. The terrain data generation pipeline utilizes multiple tools to accomplish this. Some of these are commercial tools, such as Bentley's ContextCapture photogrammetry tool. Others are tools from project partners, such as ICT's (University of Southern California's Institute for Creative Technologies) STPLS+ (Semantic Terrain Points Labeling System). Other tools, developed by Leidos, include BEES (Bare Earth Extraction System) and WALL-E.

As examples of data clean up and noise removal, photogrammetry operations rely on either computed or designated 3D points that can be used to identify the same feature (or an aspect of the same feature such as the corner of a building) and its position in multiple photographs. This process establishes tie-points across collected data. Automatic designation of tie-points can fail when the images are blurry, noisy, or there is not enough overlap between images. Blur in images can be the result of slow shutter speed, fast drone movement, incorrect focus, shallow depth of field caused by wide aperture, or light diffusion caused by narrow aperture. Correcting blur-related artifacts is often very difficult and can take considerable effort. In these cases, it may be more effective to use such images in a limited way. The alternative is to involve human operators to assist in identifying and marking the tie points; however, the use of blurry images can propagate the poor quality. Noise removal is a function of type and amount of noise (and/or the presence of additional information that can compensate for the noise). In general, recovering useful data from noisy or blurry images (for generating high-resolution end-use data products) is more burdensome than effective.

The absence of sufficient tie points often produces the type of automatically generated 3D geometry commonly known as "melted ice cream" (see Figure 7). This happens when algorithms cannot distinguish between edges of an object, and the surfaces (and their textures) blend into each other. Features such as trees or buildings that seem to melt into terrain are difficult to detect, separate, and remove from the terrain surface. This is because the slope of the melted features appears as gradual changes in terrain surface, with hill-like characteristics. The BEES tool uses algorithmic methods to detect these anomalies by analyzing the curvature of the mesh. Mesh roughness is determined by analyzing the areas near a point. High frequencies in elevation change indicate the presence of features (e.g., tree, building) that are not just the "bare earth" surface. Having sufficient overlap (roughly 70%) between collected images helps with better identification of tie points, resulting in easier determination of surface discontinuities. However, even with tie points, tools (e.g., BEES) are still required to detect the edges when the generated 3D geometry from images blends the objects into each other.

Figure 7 – Example of Melted Ice Cream Data

As part of the automation strategy, AI-based solutions for fixing the data are being evaluated. For example, neural networks can be trained to identify objects that are not of interest. This can include transient/temporal content such as cars. It can also include detection of errors such as sinkers, floaters, or shears (melted ice cream effect) in mesh content generated from insufficient image angles. It is expected that such techniques can aid in identifying and removing some of the undesired content (an example is shown in Figure 8). However, additional evaluation is needed to ensure the results are dependable and have not removed useful data.

Figure 8 – Reconstructed Mesh with Transient Objects (Left) and with Transient Objects Removed (Right)

FINDING, ADJUDICATING, AND EXTRACTING THE RIGHT DATA

Feature Identification Approach

With anomalies and noise removed from the collected data, the next step is to detect and identify natural and man-made features in whole. The strategy for this step is to focus on specific content, such as regions of specific type of land surface, transportation networks (e.g., roads, rivers), buildings, and individual objects or structures (e.g., trees, poles/bollards, traffic signs/lights, building components). In each case, it is key to detect and identify object surfaces; for example, walls or attached building components. Automatic correlation of objects and components is done by using additional information such as spatial relations and material attributes (Moore, Reilly, & Pelham, 2018).

Algorithmic tools such as BEES are used to separate terrain from all other features (buildings, vegetation, free-standing walls, fences, gates, poles, and other man-made or natural features). The input into BEES is the output from photogrammetry-based tools that produce a mesh. This includes the digital surface model (DSM) produced from the collected site data. In effect, the DSM is the top/exposed surfaces of everything visible, as if a cloth is draped over everything in the area. This mesh contains the top surface of all features and terrain. The task is then to separate the various surfaces and their underlying objects, such that each object can be processed and represented with additional detail. For example, objects such as buildings can be made into distinct separate models, with attributes and geometry that can be used or altered during simulations. To separate the terrain from features, BEES needs to determine what is and is not terrain. This is relatively easy when a feature is distinguishable and different than terrain – highly geometric shapes such as clearly vertical walls, fences, and poles are good examples. However, this requires the data to contain crisp boundaries between objects, which is not always the case. By contrast, it is much harder to separate features such as vegetation, since the geometric separations are less distinct, more organic, and tend to flow with the shape of the terrain. Algorithms in BEES are used to separate terrain from buildings. Well-trained neural networks are used to separate other features, such as vegetation, where more traditional algorithmic approaches exhibit difficulty. The techniques used to find features can also be used to pick out components of buildings such as doors, windows, sills, and balconies.

Specialized Techniques

Ongoing work is combining AI/ML techniques with traditional algorithmic methods to develop an automated process for generating high-resolution and high-quality terrain data products. Algorithmic methods can be used to solve certain problems in a much more straightforward, cost-effective way than AI/ML techniques. AI/ML techniques can be focused on specific problems for which algorithmic methods would be highly impractical/ineffective. The two approaches can also be used in combination to solve individual parts of a larger problem. For example, an algorithm can be used to smooth the surface of a feature when surface roughness exceeds a threshold proven to confuse neural networks. The smooth surface can then be submitted to neural networks to provide more effective segmentations.

Another technique to getting effective segmentation is to have specialized neural networks. In general, neural networks can lose effectiveness as a function of the number of object types they are trained to detect and the number of distractions they encounter. Specializing these networks to detect a small number of object types can address both challenges and lead to increased accuracy.

One strategy for detecting more complex types of objects is to use opinions from multiple sources. For example, once BEES has isolated a building, WALL-E is used to detect more detail about the building, such as walls and roofs. Neural networks trained to segment walls from the mesh are also used to generate a second source of answers about where walls and roofs are (Neuenschwander, Perry, & Magruder, 2023). With effective adjudication of these multiple results, a single final answer can be deduced that provides more confidence than an answer generated by just one approach. For example, in cases where WALL-E cannot identify the walls of a building, answers from other stages in the pipeline, such as neural network modules, are fed back into WALL-E to identify the walls. This mix-and-match approach is an example of how the combination of techniques are used in detecting and identifying more complex types of objects.

For adjudicating answers, confidence scores are computed for parts and/or the whole of each answer to reflect the estimated effectiveness of the answer. Scores can be based on empirical evidence when attainable, or on theoretical estimation when not. The scores can be used to determine the final result when adjudicating the answers from multiple sources. Once the features have been adjudicated and extracted, their geometry and associated attributes are stored in 3D form to continue refining the content in subsequent stages. Two-dimensional raster images are also used to store a flattened version of the feature types.

AUTOMATING DATA GENERATION OF END PRODUCTS

Significant improvements and techniques have been introduced during the last fifteen years to reduce the touch-labor through automation and procedural generation of some aspects of the final data products. Extending these automations to the entire end-to-end process (from data collection to fully tailored and integrated data products) is an on-going effort. Affordability of neural network computations and the continuously improving techniques for training them is enabling more comprehensive automations throughout the terrain data generation pipeline.

The goal is to use the appropriate set of tools at the right stages of the pipeline to produce accurate high-resolution data products, while keeping the process efficient and affordable. Automation plays an important role in achieving this goal, realizing that some tasks can be automated more readily, and others require incremental improvements as lessons are learned and more knowledge is gathered on the level of automation that can be applied. Therefore, automation is not always the application of AI/ML, but rather applying the right combination of techniques for specific tasks.

SUMMARY

Terrain data is a critical part of many military training systems. As such, collection, evaluation, and integration of high-quality, accurate, and current real-world terrain data are essential steps in supporting military training exercises. A better understanding of data collection challenges can lead to more accurate and, subsequently, more usable terrain data products. At the same time, data collection goals and procedures must reflect the required information at various stages of the terrain data generation pipeline.

This paper has outlined recent research activities that are addressing terrain data generation challenges through improved data collection methods and increased use of automated tools for extracting the desired data. Most notably, sufficient overlap thresholds, appropriate sensor parameters, attention to conditions during collection, and cross-correlation with other reference data are used in producing high-resolution content. Better collection procedures and capabilities reduce the need for cleanup. Yet, no collected data is error-free, and therefore benefits from the use of automated error removal and correction methods. Strategically combining the right algorithmic and photogrammetry tools with AI/ML solutions supports the generation of terrain products that can meet the needs of Live-Virtual training. The approach focuses on incremental improvements to the automation of the end-to-end process by using both algorithmic and AI/ML tools to produce accurate high-quality data products. A visualization of such final data products is shown in Figure 9.

Figure 9 – High-Resolution Terrain for Ft. Irwin, Ujen MOUT Site

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