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Engineering pedagogical content knowledge for undergraduate engineering and technology programs: Accelerating graduates' preparedness for the 4IR geospatial industry

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Abstract:
Surveying engineering technology (SET) and Geomatics (S/G) programs have significantly been impacted by advances of three-dimensional (3D) geospatial data acquisition technologies coupled with innovation in computational infrastructure over the past decade. Today, large-volume 3D data in the form of point clouds, meshes, or other representations, are frequently collected by sensors such as Light Detection and Ranging (LiDAR) and depth cameras for both industrial purposes and scientific investigations. Traditional surveying techniques are more often integrated with the emerging state-of-the-art geospatial technology and 3D data analytics. Evolving geospatial industry labor markets are challenging the traditional skillsets developed at conventional S/G programs at colleges. Yet, higher education graduates may still lack decision making and project application skills, and most importantly, the ability to apply the body of knowledge from their academic training in college courses to solve real-world problems and meet the skill challenges of the Fourth Industrial Revolution (4IR).

To bridge the gap between theory and application of these relevant technologies for industry-ready graduates, hands-on exercises are developed and will be incorporated in a 300-level photogrammetry course for SET and Civil Engineering majors. This case study describes a project-based learning exercise that requires students to process point cloud data and develop spatial literacy skills. Point cloud processing experience ramps up critical geospatial skills through using Open3D, an open-source library that supports rapid visualization and processing of 3D data, and Open3D-ML, an extension of Open3D for 3D machine learning tasks. With a few lines of Python code, students will be presented with complete workflows such as surface registration, scene reconstruction, semantic point cloud segmentation, and object detection, thus gaining a better insight into these complex topics and how they are translated into easy-to-follow operations and applied on real 3D data. It is our hope that our efforts to combine theory, real-world applications, hands-on exercises, and publicly available resources will largely enable students to immerse themselves in the learning, promote their intrinsic motivation to master S/G curricula, and empower them to become active data users and analysts in their professional career.

Keywords:
Point Clouds, Surveying, Geomatics, Spatial Literacy, Undergraduate Education, Open3D, Python, Machine Learning

1. Introduction

Surveying engineering technology (SET) and Geomatics (S/G) are fields that deal with the measurement, analysis, and management of geospatial data, which includes the location, shape, and size of natural and man-made objects on the Earth's surface. In the past, geospatial data was mostly collected using traditional surveying techniques (e.g., total stations), which were often limited to planimetric measurements that only provided information on the horizontal location of objects. The development of three-dimensional (3D) data acquisition technologies, such as

LiDAR (Light Detection and Ranging), photogrammetry, and UAVs (unmanned aerial vehicles), has revolutionized the way geospatial data is collected, processed, and analyzed. More specifically, LiDAR uses laser scanners to produce highly accurate 3D point clouds, photogrammetry uses aerial photographs to create 3D models of objects and terrain, and UAVs equipped with cameras or LiDAR systems can capture high-resolution 3D data from inaccessible or hazardous regions. Such technologies have enabled S/G professionals to collect large amounts of accurate and precise geospatial data in a relatively short period of time. Meanwhile, the innovation in computational infrastructure has also played a critical role in the S/G advancement. The availability of high-performance computing resources, cloud-based data storage and processing, and advanced software tools for data analysis and visualization have made it possible to process and analyze the large volumes of geospatial data acquired by 3D technologies in a timely and efficient manner, allowing S/G professionals to extract meaningful insights from the data (e.g., identifying data patterns, trends, and anomalies). Thus, S/G programs have been significantly impacted, leading to new opportunities for innovation and discovery in a variety of fields such as urban planning, environmental monitoring, and natural resource management.

Large-volume 3D data in the forms of point clouds, meshes, or other representations, can be collected through sensors such as LiDAR and depth cameras. To take advantage of the benefits arising from the use of large-volume 3D data, traditional surveying techniques are more often integrated with the emerging state-of-the-art geospatial technology and 3D data analytics, offering a powerful toolset for S/G professionals to capture and analyze highly detailed and accurate geospatial data. Recently, there has been a significant increase in the use of large-volume 3D data for various industrial purposes (e.g., product design, quality control, and inspection) and scientific investigations (e.g., archaeological/geological survey), showing the potential to assist with decision making and transform the way humans see and understand the world.

The geospatial industry is undergoing rapid transformation due to technological advancements, leading to significant changes in the types of skills and knowledge that are required by professionals working in this field. This, in turn, is challenging the skillsets that have been developed through conventional S/G programs at colleges. For several decades, S/G programs have been focused on teaching students the fundamentals of surveying, cartography, and geographic information systems (GIS), along with related technical skills such as using surveying equipment as well as data processing and map making software. The programs have been designed to provide students with a strong foundation in the principles and practices of land surveying and mapping. However, the demand for new skills and knowledge has emerged with the evolution of the geospatial industry. For example, there is now a growing need for professionals who can process and analyze large volumes of 3D data, and who can use the technologies for 3D geospatial data acquisition. As a result, traditional S/G programs are being challenged to keep pace with these new developments and provide students with the skills and knowledge that are required by the evolving geospatial industry. Colleges offering these programs are now under pressure to update their curricula and incorporate new technologies and skills to ensure that their graduates are prepared for the changing labor market.

Moving into the Fourth Industrial Revolution (4IR), the need for higher education graduates to have decision making and project application skills is more recognized than ever. The 4IR is characterized by the convergence of technologies, such as artificial intelligence (AI), the Internet of Things (IoT), and robotics, greatly transforming the way humans live and work. In this context, an increasing demand has emerged for professionals who not only have a strong technical foundation but also can solve complex problems and make informed decisions. Nonetheless, one challenge that S/G graduates often face is the gap between academic training and real-world applications. While students have learned the necessary technical skills in college, they may not have had the opportunity to apply the body of knowledge in a practical setting. Addressing this challenge generally requires colleges offering S/G programs to incorporate project-based learning opportunities into their curricula. Such opportunities provide students with hands-on experience and help develop their critical thinking and problem-solving skills that are essential for a successful career in today's evolving geospatial industry.

2. LiDAR Point Clouds

A point cloud is essentially a huge collection of individual points in 3D space. Each point in the cloud corresponds to a specific location, and may also include additional information such as intensity values. Once a point cloud is generated, it can be processed and analyzed using various algorithms to extract useful information for purposes of object recognition, segmentation, and surface reconstruction (e.g., [1-3]). Different from a triangle mesh, a point cloud does not require to store the polygonal-mesh connectivity [4] or maintain topological consistency [5]. Therefore, processing and manipulating point clouds usually demonstrate better performance and lower overhead [6]. Today, point clouds have become increasingly prevalent in many research fields, such as computer vision, robotics, and GIS, as they provide a powerful capability to represent the geometry of real-world objects or environments. Some common applications of point clouds include creating 3D models of buildings, generating terrain maps, or analyzing the shape of complex objects.

Point clouds can be generated through a variety of methods, such as using laser scanners or depth sensors. In recent years, Light Detection and Ranging (LiDAR) has been widely applied to collect point cloud data due to advancements in technology that have made LiDAR sensors more affordable and easier to use. LiDAR works by emitting laser pulses, measuring the time it takes for the pulses to bounce back after they hit an object, and using the time to calculate the distance from the sensor to the object. This process is repeated many times per second, creating a dense 3D map of the environment with detailed and precise information about the shape and structure of objects. LiDAR can be placed on a variety of airborne, ground-based and marine platforms to collect data from the air, ground, and underwater, respectively. Selection of the platform depends on the specific application and the desired level of detail and accuracy. For example, airborne LiDAR can cover large areas quickly but may not be able to capture small-scale details, thus is commonly used for topographic mapping and forest inventory. In contrast, ground-based LiDAR data collection with sensors mounted on tripods or autonomous vehicles can capture much more details but is generally slower and more labor-intensive, thus is often used for infrastructure inspection and monitoring. Because LiDAR point clouds can be very large and complex, specialized software packages and open-source libraries are often required to process and analyze the data, either independently or combined with other types of data (e.g., images), for a more complete understanding of a given environment or object.

3. Pedagogical Framework for 4IR Geospatial Industry

Recent advances in computational capabilities and geo-sensing technologies are poised to play an important part in the 4IR that promises to shape a new era [7]. These advances have a direct impact on S/G education and career preparation. Data-intensive geospatial computing, visualization, and geo-sensing technologies, such as the integrated Global Positioning and Inertial Navigation Systems (GPS/INS), terrestrial and airborne LiDAR, laser tracking and sophisticated terrestrial laser scanning (TLS) devices for Scan-to-BIM (Building Information Modeling), mobile mapping, digital photogrammetry, satellite altimetry, and multi/hyperspectral mapping, have advanced in leaps and bounds and opened up new career paths that will revolutionize human interaction and workforce skills in the digitalized world (e.g., [8-11]). Indeed, the education of young people who are faced with situations in today's technocentric and problematic world must be reoriented towards developing appropriate thinking, reasoning, and decision-making skills [12].

The Geospatial Technology Competency Model (GTCM) [13] describes the competencies that university programs should develop in order to meet the 4IR workforce needs. However, the competencies outlined by GTCM and its application in traditional undergraduate curriculum development for geospatial science, engineering and technology programs require a pedagogical framework conducive to nurturing spatial literacy [14]. The 4IR careers involve a wide range of spatial cognitive processes, including spatial perception, visualization, and reasoning, as the required tasks are performed in space [9, 15]. Therefore, re-tooling for a new generation workforce can provide useful learning opportunities on spatial literacy in schools, colleges and universities [16]. The S/G curricula are heavily involved in metrology, graphical communication using computer aided drafting (CAD) and GIS technologies, 2D, 3D and 4D modeling from point cloud data and imagery, and error analysis. Such experiences when brought into the classroom can add value to career preparation of college-bound students.

In particular, working with digital point clouds is formidable due to their sheer size and complexity, thus requires specialized skills, resources, and expertise. In any event, integrating point clouds in the Scan-to-BIM workflow is an invaluable skill for the 4IR workforce. The end product of point cloud processing is often a 3D virtual reality model of the scanned object or scene. To achieve this, the first step is to stitch two or more point clouds together, and this process is typically referred to as point cloud registration (PCR). However, the PCR task of S/G student capstone project proved very tedious during common target point selection for input to compute the transformation (i.e., combination parameters). While AI has the potential to make a seemingly intractable big (geospatial) data problem more manageable, the learning curve is very steep for undergraduate students due to the multidisciplinary nature of the field and the huge volume of unreferenced points without spatial context. The skills required to achieve successful student learning outcomes are driven by competence in spatial literacy.

Spatial literacy has roots in mechanical aptitude and is considered an indicator of intelligence. Low retention rates of students in STEM have been related to their poorly developed spatial skills [12, 17, 18]. Today, spatial literacy is understood as an amalgam that involves understanding in three related components: the nature of space, the methods used to represent spatial information, and the processes of spatial reasoning (e.g., [19] and references therein).

While researchers generally agree on the importance of spatial literacy and that it comprises more than one skill, there is surprisingly little consensus about the details of what make up this skill set and its associated thinking modalities [16, 19]. Spatial literacy therefore remains highly investigated and controversial with no consensus on its definition. Nevertheless, the emerging understanding is that spatial literacy plays a gatekeeping role in the success of STEM careers (e.g., [12, 20]).

4. Nurturing Spatial Literacy

Teaching and learning, at their most fundamental and mechanistic level, are neurological phenomena arising from physical changes in brain cells. Brain research findings suggest that spatial literacy in humans can be highly developed because the human brain builds a unified representation of the spatial environment, known as a 'cognitive map', to support memory and guide future action [21]. Cognitive maps are neutrally instantiated by place, grid, border, and heading/direction cells in the brain. The neural instantiation of a spatial map takes the form of a Euclidean coordinate system that allows landmarks to be encoded in terms of their allocentric locations (i.e., the spatial information about the position of objects relative to each other) [21, 22]. These brain cells are the building blocks for core human spatial reasoning and thought. The notion that learning and memory are neurobiological processes provides opportunities to explore how pedagogical techniques might harness these known neurological processes to create and retrieve new (geospatial) thinking patterns in STEM education. Learning is possible because the brain creates memories through altering the synaptic connections between specific neurons, stores them in connected ensembles of neurons, and retrieves them by reactivating those same neurons and connections [23].

A recipe for nurturing spatial literacy as a 4-step process includes self-efficacy, context, scale and pedagogy [16]. First, self-efficacy (i.e., gender, experience, age, culture, and education) plays a role in spatial literacy. Second, context matters because spatial skills are performed in a natural and physical environment. Third, scale controls the amount of information conveyed and/or processed. We acknowledge that spatial thinking without environmental context is limiting because scale and context allow one to differentiate between thinking in space versus thinking about and with space [24]. Fourth, task analysis and alignment is critical, and learning tasks as outlined in program curricula must be aligned with activities that support student outcomes. Finally, teaching and instructional designs matter. A detailed discussion on this topic is beyond the scope of this article but we draw on the essential elements in this field to focus teaching on spatial literacy via geoscience and in particular S/G curricula.

Pedagogy plays an important part in developing spatial literacy. Cognitive Load Theory (CLT) provides a framework for designing instructional materials and is focused on identifying instructional designs that can effectively reduce cognitive burden on the learner (e.g., [25]). According to CLT, ineffective cognitive load results from instructional techniques that require learners to be engaged in working memory activities that are not related to schema construction (e.g., [26] and references therein). Extraneous cognitive load is imposed by the way information is presented. Therefore, educators and instructors should acknowledge that cognitive load is controlled by instructional design and can be modulated by it. CLT presents the major building blocks that emphasize instructional design that reduces extraneous cognitive processing, namely

a) remove barriers to learning by reducing cognitive loads of complex tasks, b) invoke instructional design with real-life tasks to incentivize learners and drive forces for complex learning, and c) apply methods of adaptive learning to progressively assess expertise development by examining the levels of effort and the schemata followed in problem solving.

The level of complexity of a concept depends critically upon the way in which it is taught. To achieve simplification, instructors must find the right representation. In line with CLT, visualization enhances comprehension because graphics can reduce extraneous cognitive processing (e.g., [26] and references therein). Managing levels of complexity also depends on the ability to deconstruct the hierarchy of schemas or of a complex system (e.g., [26] and references therein). The CLT framework is well suited to guide the application of the TSSL (task, semantics, syntax, and lexicon) model for teaching and learning the body of knowledge of S/G education. The TSSL is a multilayer model to be exploited by instructional designers to help learners accomplish specific tasks. The TSSL model supports the interaction between humans and technology in either a top-down and bottom-up implementation. A top-down implementation demands that the highest levels (i.e., low complexity) be set first, followed by more detailed analysis. A bottom-up implementation allows low-level elements to be generated first, in a process referred to as "working forward" (e.g., [26] and references therein). Most traditional surveying problems are solved by top-down approach, but newer topics like GIS database design involves the integration of both top-down and bottom-up approaches [27].

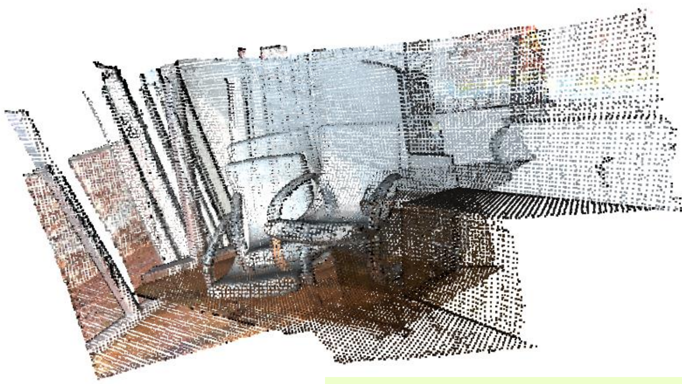
5. Case Study

We use Open3D and Open3D-ML [28] to explore the infusion of AI in undergraduate S/G education to bridge the gap between theory and application for industry-ready graduates. Specifically, hands-on exercises are developed and will be incorporated in a 300-level photogrammetry course for SET and Civil Engineering majors offered within the SET program at the New Jersey Institute of Technology, starting from Fall 2023. This case study presents a project-based learning opportunity that requires students to process LiDAR point clouds and develop spatial literacy skills including the abilities to identify and interpret spatial patterns, understand and use spatial scales and measurements, and communicate spatial information effectively. The focus of using this example is to demonstrate the thinking modalities imposed by digital workflow of acquisition and processing of modern point cloud data.

Point cloud processing experience ramps up critical geospatial skills through using Open3D, an open-source library that supports rapid visualization and processing of 3D data, as well as Open3D-ML, an extension of Open3D for 3D machine learning tasks. With a few lines of Python code, students will be presented with complete workflows such as surface registration (e.g., Fig. 1), scene reconstruction, semantic segmentation (e.g., Fig. 2), and object detection, gaining a better insight into these complex topics and how they are translated into easy-to-follow operations and applied on real 3D data. Moving forward, students will also be guided to process point cloud data acquired by a LiDAR system mounted on a remote-controlled wheeled vehicle to scan the hallway of the department. It is our hope that our efforts to combine theory (mostly conveyed during lectures), real-world applications, hands-on exercises, and publicly available resources will largely enable students to immerse themselves in the learning, promote their intrinsic motivation to master S/G fundamentals, and empower them to become active data users and analysts in their professional career.

We will assess the impact of our project-based learning on improving student learning outcomes of fundamentals and applications of photogrammetry. Two mechanisms, an instructor-based assessment on students' performance and a student-provided survey, will be employed to test whether students that participate in the project show difference performance than non-participating students. Details about the assessments will be reported in a follow-up study.

```
voxel_size = 0.02
pcds_down = load_point_clouds(voxel_size)
o3d.visualization.draw_geometries(pcds_down,
                                  zoom=0.3412,
                                  front=[0.4257, -0.2125, -0.8795],
                                  lookat=[2.6172, 2.0475, 1.532],
                                  up=[-0.0694, -0.9768, 0.2024])
```



```
print("Transform points and display")
for point_id in range(len(pcds_down)):
    print(pose_graph.nodes[point_id].pose)
    pcds_down[point_id].transform(pose_graph.nodes[point_id].pose)
o3d.visualization.draw_geometries(pcds_down,
                                  zoom=0.3412,
                                  front=[0.4257, -0.2125, -0.8795],
                                  lookat=[2.6172, 2.0475, 1.532],
                                  up=[-0.0694, -0.9768, 0.2024])
```

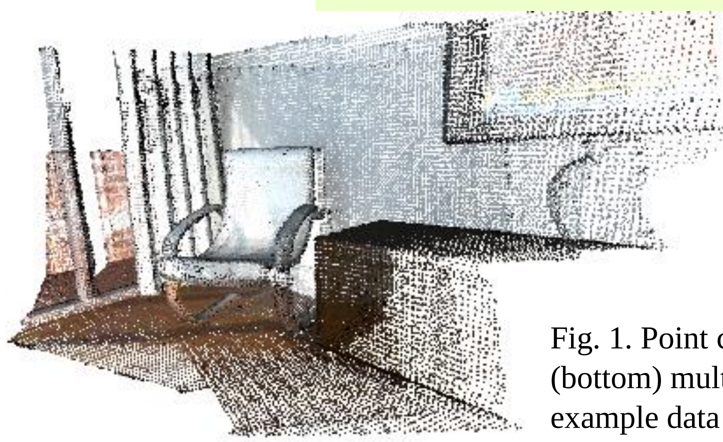


Fig. 1. Point cloud data before (top) and after (bottom) multiway registration [29] applied (using example data and code provided by Open3D).

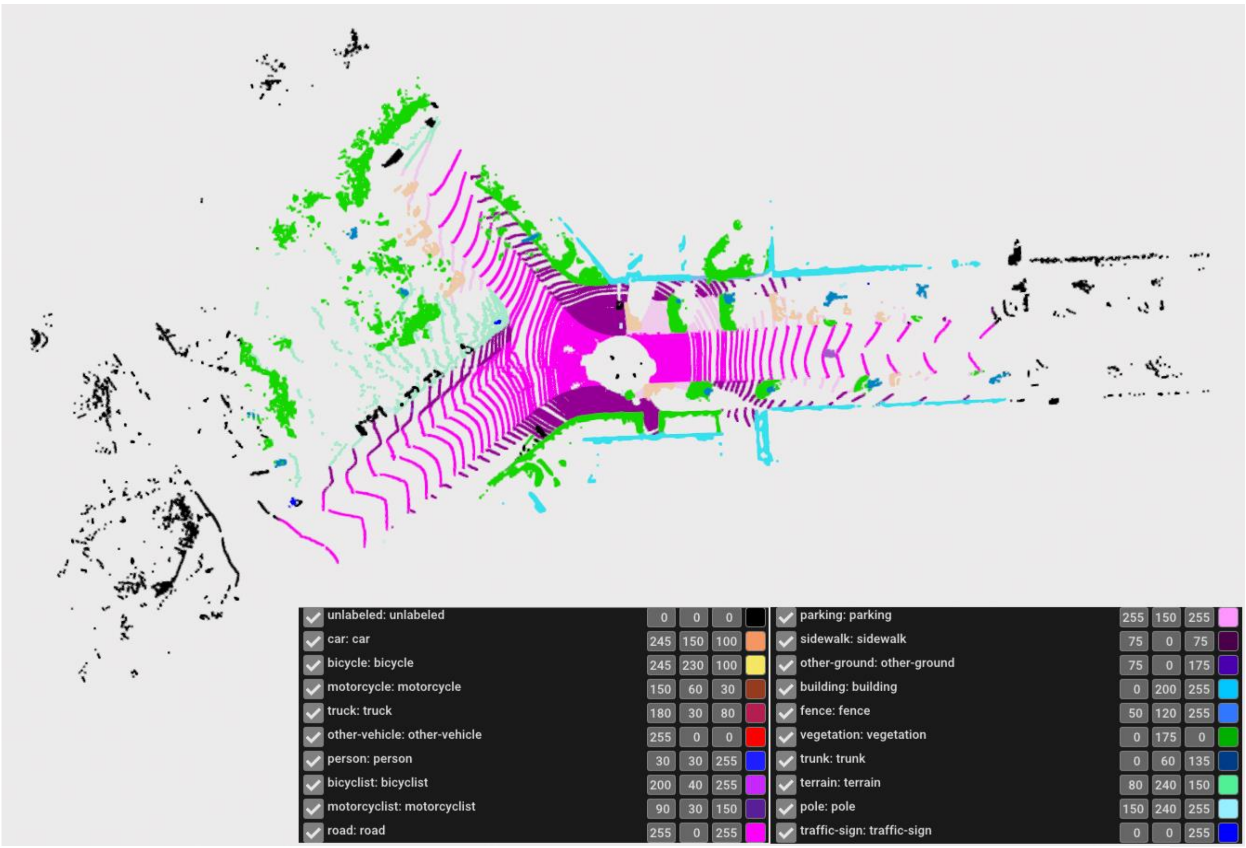


Fig. 2. Sematic segmentation of the SemanticKITTI dataset [30] using Open3D-ML.

6. Conclusions

Improvement in pedagogy can include the mixture of classroom instruction and outdoor movement and learning. While S/G is closely related to civil engineering and others, the skills required in S/G careers are not confined to only reasoning modalities within a particular STEM field such as design thinking from engineering or critical thinking prevalent in the science domain of STEM. Being a critical skill for navigating and understanding the complex spatial relationships that shape our world, spatial literacy is considered a fundamental skill of experts in STEM and a key aspect of the learning process for school students. By developing strong spatial literacy skills, individuals can become more effective problem-solvers and decision-makers in a wide range of fields and applications. The S/G education in universities and colleges today needs to enhance students' spatial literacy development through different avenues such as project-based learning and hands-on exercises in preparation for the future technically astute workforce.

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