STEVENS INSTITUTE OF TECHNOLOGY 1870

Ph.D. DISSERTATION DEFENSE

Candidate: Daniel Tafone
Degree: Doctor of Philosophy
School/Department: Charles V. Schaefer, Jr. School of Engineering and Science / Physics
Date: Thursday, April 24th
Time/Location: 5:00pm/ Babbio 221
Title: Remote Material Characterization with Single Photon LiDAR

Chairperson: Dr. Yuping Huang, Department of Physics, School of Engineering & Sciences

Committee Members: Dr. Yong Meng Sua, Department of Physics, School of Engineering & Sciences
Dr. Rainer Martini, Department of Physics, School of Engineering & Sciences
Dr. Annie Xian Zhang, Department of Mechanical Engineering, School of Engineering & Sciences

ABSTRACT

The field of active imaging has advanced rapidly in recent years, driven by its critical role in the emerging autonomous era. Light Detection and Ranging (LiDAR) systems have been significantly developed to provide accurate three-dimensional representations of the environment. However, this is only a first step toward comprehensive scene analysis, as true understanding requires more than just spatial awareness—it also necessitates an understanding of the material properties of objects. For instance, an autonomous car must treat a pedestrian with more caution than a tree, a robotic arm must handle glass carefully, and a security system must identify sharp metallic objects as threats while disregarding mundane materials.

This dissertation enhances the capabilities of single-photon LiDAR to not only provide high spatial resolution but also to extract information about the materials it targets, even in the presence of obscurants. We achieve this by iteratively developing optical imaging systems of increasing complexity, focusing on the identification of key material properties despite severe limitations.

Our first study explored single-point, single-pixel classification by leveraging time-of-flight (ToF) LiDAR scanning and machine learning to differentiate between porous materials. Using only one dimension of information, we achieved a classification accuracy of 97.8%, which persisted at 96.1% even in the presence of an obscurant with an optical density (OD) of 4.8 (9.6 OD round-trip).

In the next iteration, we introduced raster scanning, enabling us to capture all three spatial dimensions. The complexity of our targets was increased to include common materials. By extracting material-specific reflectance and surface texture data, we achieved a classification accuracy of 99% under optimal conditions and 89.17% in obscured scenarios with up to 7.6 OD (15.2 OD round-trip).

Moving beyond classification, we began measuring defining material characteristics such as surface roughness. We developed novel techniques using a raster scanning, single-pixel system paired with a regression model to measure surface roughness values ranging from 1.21 to 102 microns, with an average error of 8.7 microns.

Finally, we introduced a multi-pixel detector, utilizing fast optical gating and picosecond resolution, to identify new features that fluctuate across depth scans. These features, which provide key information about the target's surface roughness, are resilient to visual obstruction and scattering, allowing for sub-micrometer resolution insights.

The findings of this dissertation have significant implications for AI-driven applications, including autonomous navigation, security screening, and biomedical diagnostics. By enhancing the extraction of material-specific information from previously collected data, this research bridges the gap between quantum optics and machine learning, paving the way for future advancements in intelligent sensing technologies.