EASEEbot: A Robotic Envelope Assessment for Energy Efficiency

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***Abstract*— Building envelope inspections are necessary to maintain buildings' energy efficiency, but current solutions are expensive, time-consuming, and destructive. Furthermore, inspectors often face safety and accessibility issues. To mitigate these issues, we propose a holistic system, EASEEbot, consisting of robots to capture data and help retrofit and employ artificial intelligence to assist in data analysis. The robots including an unmanned aerial system (UAS) and ground-penetrating radar (GPR) accommodate data collection while the Robo-dog offers guidance to inspectors in retrofitting phase. The machine learning algorithm helps to analyze the captured data, identifies envelope issues, and generates a building's digital twin to map identified defects spatially to buildings' façades. The retrofit Robo-Dog uses the generated digital twin to project previously recorded defect imagery onto corresponding areas of the building's envelope. It further guides workers to ensure the identified defective areas are addressed. EASEEbot offers non-destructive sensing, risk mitigation, and high-quality building envelope inspections.**

***Index Terms*— Unmanned Aerial System, Wall-climber, Building envelope**

I. Introduction

Reductions in energy usage and carbon emissions became mandatory with stringent regulations enacted by municipalities nationwide. Now, building owners are required to reduce their emissions to avoid fees and they already have reached maximum efficiency in their mechanical and electrical systems, so their focus has shifted to diagnosing building envelope issues and retrofitting. Identifying building envelope issues and proposing solutions are possible only with high-quality building envelope inspections and energy audits. Current methods mostly depend on ground-based or handheld infrared thermography (IRT) to detect building envelope defects [1]. However, for a large-scale inspection, inspectors often face safety hazards, extra instrument cost and accessibility issues which highlights that solutions must be non-destructive, act as a productivity multiplier, mitigate risk, and produce high quality results.

In this paper, we propose a system of a Robotic Envelope Assessment for Energy Efficiency (EASEEbot). EASEEbot consists of robots and AI for building envelope inspections and analysis to assist inspectors at every stage of the building retrofit process. At a high level, there are three stages of EASEEbot, namely data capturing, data analysis, and retrofitting. During the data capturing stage, EASEEbot utilizes an UAS and a GPR; later, the captured data is analyzed during the data analysis stage, and finally, EASEEbot Retrofit Robo-Dog aids workers and inspectors during the retrofitting phase. The EASEEbot UAS safely flies around a building and non-destructively captures color and infrared imagery in a fraction of the time of a conventional inspection. This data is processed by the EASEEbot's thermal AI to detect envelope issues such as trapped moisture, air leaks, and thermal bridges. Attaching the EASEEbot radar module converts the UAS into a wall climber and allows users to find previously undetectable envelope issues (i.e., deep moisture penetration and corroded wall ties) in a non-destructive fashion. The dataset is further processed and then fed to the EASEEbot's 3D reconstruction algorithm to generate a digital twin of the inspected scene and map it out as a 3D point cloud of the exterior façade - scanned imagery data is organized by its 3D pose. These analyses enables inspectors to make informed decisions easily on where and how to retrofit and repair building envelopes. During retrofitting phase, the EASEEbot Retrofit Robo-Dog uses building information models procured from previous 3D point cloud scans to visualize the previously recorded and detected defects onto corresponding surface areas of the building's envelope through a projector-based augmented reality system on the Robo-Dog. In the process, it guides construction inspectors and retrofit workers to ensure those defects are properly addressed. The Retrofit Robo-dog makes it easy for workers to understand where issues are and conveys context-specific retrofitting information related to those issues.

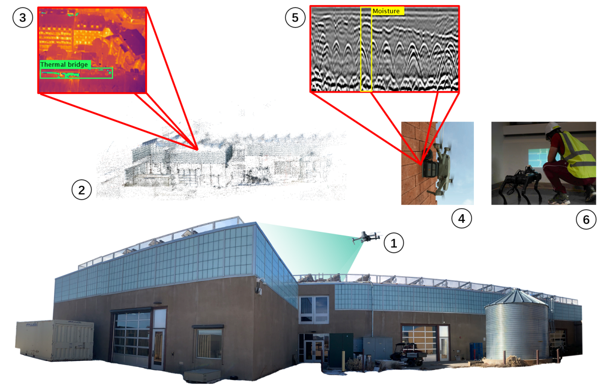

Fig. 1: Illustration of the EASEEbot system: 1. RGBT data capture; 2. 3D RGBT point cloud; 3. Thermal bridge detection; 4. GPR scanning by UAS wall climber mode; 5. Moisture detection; 6. Robo-dog retrofitting assistant

II. Related Work

Drones & Thermography: Research is being conducted on infrared scans of building envelopes conducted by drones [2]. A literature review reveals that authors have explored automated ways of detecting thermal anomalies. These initial attempts make use of the superpixel method of clustering neighbouring image pixels with similarities [3]. Other attempts at creating an automatic anomaly detection algorithm for building envelope issues incorporate segmentation neural networks [4]. However, these approaches do not differentiate between different types of building envelope failures and

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such as failed insulative double paned windows, acceptable thermal bridges on rooftops due to the presence of mechanical units, or open windows that show a hot spot. Another unexplored area is training a neural network to understand the difference between positive and negative scans of a building. Positively pressurizing a building (turning the HVAC on such that there is more pressure inside the building than outside) allows a thermal scan to detect air leaking out of a building. Negatively pressurizing it prevents a thermal scan from detecting air leaking out of the building. A subtraction of the two images should isolate for thermal bridges, and a subtraction of this image with the positively pressurized building scan should isolate for areas of air leakage. This is currently done manually by industry engineers, without the widespread use of computer-based image processing aids.

GPR: In the building space, microwaves have been extensively used for detection and analysis. GPR and through wall imaging radar use microwaves to detect covered and buried objects. Microwave-based radar has been used extensively to find buried pipes and rebar embedded in concrete [5]. Pipe and rebar detection works by establishing a baseline microwave reflectance signal and searching for differences from that baseline. Based on this principle, microwave-based radar has also been used for detecting moisture in building components [6]. Through more complex signal analysis, it has been extended to tracking people behind walls and extracting the internal structure of a wall assembly itself [7]. Researches have applied supervised deep learning algorithms to automatically extract relevant hyperbola information from GPR scans, but their models are geared towards detecting buried pipes and utility lines [8]. Using GPR to detect moisture and exploring how well machine learning algorithms can capture this information would expand the current body of knowledge.

III. Methods

The experiment platform includes UAS flight mode, UAS wal climber mode and retofit Robo-Dog as the hardware, Thermal AI, GPR AI and 3D Reconstruction Algorithm as the software.

A. Hardware

1) UAS flight mode: As the primary mobile platform for data collection, UAS flies with sensors and follows preset flight trajectories. The EASEEbot UAS is designed to be foldable. Bounding box dimensions are 8.43 × 3.58 × 3.31 inches (L×W×H) for folded and 12.68 × 9.53 × 3.31 inches (L×W×H) for unfolded. An integrated dual-lens sensor module, which has a 640×512 resolution uncooled VOx microbolometer and a 4K RGB color camera, is attached to the UAS with a gimbal. The UAS also has a micro-USB port on the top of the fuselage to transmit additional sensor data or provide power to the beacon for night flight. There are six cameras and two linear LIDAR sensors installed on the fuselage, which are used as the sensor input for the automatic omnidirectional obstacle avoiding system.

2) UAS wall climber mode: When switching to the wall climber mode, the UAS needs to be connected to a tether system and the GPR sensor. The tether is attached to the wall out of safety concern. The GPR sensor is to be installed under the center gravity of the UAS, fixed with 3D printed holder. Meanwhile, the gimbal on the UAS can remain attached, due to the infrared camera sensor module's compact size. The UAS needs to take off from an orientation parallel to the building façade. Prior to take off, the UAS's onboard inertial measurement unit (IMU) and the automatic omnidirectional obstacle-avoiding system will need to be disabled. One LIDAR sensors attached on the bottom of the fuselage will detect the distance between the fuselage and wall and control the motor's throttle to ensure the GPR touches firmly on the building façade.

3) Retrofit Robo-Dog: The EASEEbot Retrofit Robo-Dog's flexible legs can navigate around these obstacles better than crawling and wheeled robots. Our robot dog has four high torque motors to control each leg and body pose individually. Meanwhile, we installed a ball-shaped force sensor on the "feet" of each leg, which provides a feedback signal to estimate the pose of the robot dog and the level of the ground. At the front of the robot dog, we installed a distance perception module, including a Lidar and a dual-lens 3D camera. This module assists the Retrofit Robo-dog in mapping, localization, and navigation. We set three main control components inside the robot body: a battery pack, an Nvidia Jetson Xavier NX single-board computer, and Intel NUC mini PC. The Nvidia Jetson is responsible for the sensor data collection, feedback processing, attitude estimation and simple visual obstacle avoidance. The Intel NUC handles more complex program computation, such as map generation, path planning, robot-environment interaction and communication. In order to project the defect points on the construction wall, a projector-based augmented reality (PAR) module [9] is installed on the back of the robot dog. The PAR module consists of a compact projector and Intel Realsense T265 camera. We use a T265 camera as visual input for high-precision visual odometry and a projector as image output from Intel NUC. In addition, the robot dog also has a remote controller and a simple control app for manually remote control.

B. Software

1) Thermal Camera Calibration: There have been a number of different attempts at performing geometric camera calibration of a thermal camera. Most solutions use a checkerboard as a camera calibration rig. Some solutions exploit different material emissivity properties to produce a contrast [10]. This is appropriate in some settings, but others find that they need to further increase the contrast between the black and white squares of the checkerboard in order to obtain good results. Their solution was to use computer vision techniques to increase the detectability of the squares and their corners so that a more robust camera calibration could be achieved citeshibata2017accurate. We tested multiple methods involving active and passive heating

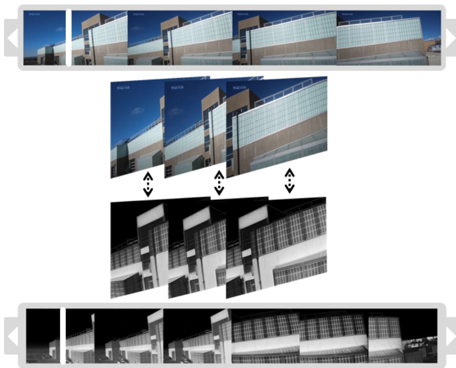


Fig. 2: RGBT image precessed into RGB image and Thermal image

on various materials. We used a lasercut acrylic checkers with a carboard backing, lasercut wood checkerboard with a vinyl backing, and machine cut vinyl with a metal backing. We tested each with and without active heating.

2) Thermal AI: EASEEbot's thermal AI algorithm is a modified UNet [11] algorithm created using PyTorch. An image is input as a 4 channel tensor composed of RGB and Thermal channels. Prior to image analysis, thermal and RGB scans taken during UAS inspections are registered with the shooting location and concatenated into a 4 channel RGBT scan video. The scan videos are then sectioned into individual frames, which form a video-specific dataset. The video-specific dataset is fed into our pretrained neural network model to create segmentation masks for detected thermal and moisture anomalies. The segmentation mask is a binary channel picture of the same size as the input RGBT image where every pixel corresponds to the pixel in the image; the top right hand pixel in the RGBT image corresponds to the top right hand pixel in the segmentation mask. Where the AI algorithm has detected a thermal anomaly, the value of the pixel is 1 and the rest is 0. The RGBT image is then processed back into separate RGB and T data streams. The segmentation masks are applied as an outline to both RGB and T data streams and reviewed to ensure that all masks are accurate. The RGB image stream is further processed - segmentation masks are filled in as bright yellow. The processed RGB images are then sent to the 3D reconstruction algorithm.

3) GPR AI: GPR is a non-destructive sensing and inspection tool that has traditionally been used to find buried utility pipelines in the ground and metal embedments within concrete. the GPR unit emits radio-frequency waves and records the time and intensity of reflection. We attach the Proceq GP8800 unit to EASEEbot and connect it to their iPad. GPR readings are taken along a wall surface and automatically tracked by Proceq's data capture system on the iPad. Once the wall climber has completed its scan, the scan data is exported from the iPad to our server. Scans are then sent through our GPR-specific AI to label anomalous areas which indicates whether moisture is present within the envelope's assembly. The GPR scans are put through a binary convolutional network. A convolutional neural network (CNN) convolves through the scans to label an approximately 1 ft section as either anomalous or normal. The network is a modified UNet model. The output layer has a sigmoid activation function that makes the final anomalous/non-anomalous determination of a scanned section.

4) 3D Reconstruction Algorithm: EASEEbot's 3D reconstruction algorithm is based on the structure-from-motion (SfM) algorithm. While the UAS is in flight, images are captured every 15 to 25 frames in RGB color and infrared videos, while onboard GPS records the location of the UAS cameras and their viewpoint direction for when each image is captured. The capture interval depends on the complexity of the building envelope. Once all the images are captured, feature points are extracted from each image through a pre-trained machine learning neural network. By identifying common feature points shared between pairs of video frame images, and knowing the difference between the two images' respective camera 3D locations and viewpoint directions, the 3D location of those feature points can be inferred. The GPS data associated with each image, as well the timing of each image in videos can be used to initially group the images by rough general locations in 3D space. An additional graph neural network and attention mechanism are used for matching feature points among locally grouped images. A global list of feature point matches is then compiled by tabulating common feature points over all localized groups of images. Using this global list of common image-feature points and calculating all matched images' respective differences in camera translation and rotation, the algorithm estimates the 3D location of each feature point, and a sparse 3D point cloud is generated. Noise in 3D point cloud estimations are reduced by bundle adjustment, which tries to make the point estimations more consistent over the entire scan.

IV. Experiment

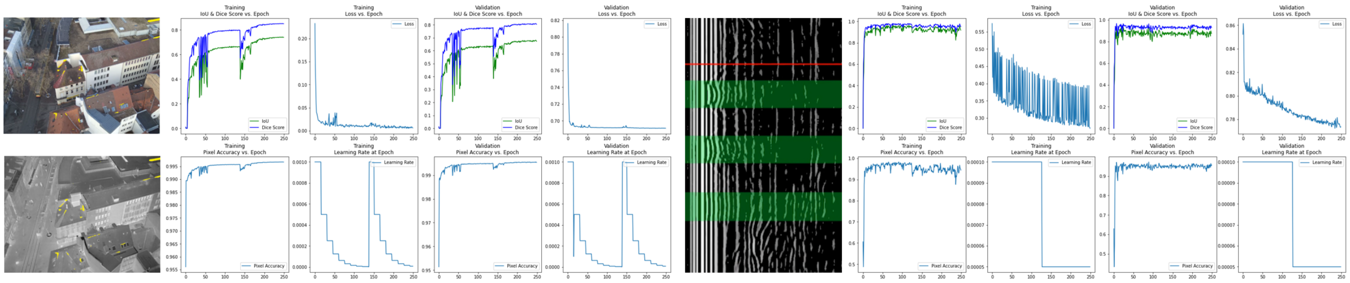
With our experiment platform, we validate our software by performing following experiments

A. Thermal AI experiment

Thermal AI is a UNet model trained over the Mayer dataset [12]. Trained the model for 250 epochs. The learning rate was halved every 15 epochs. Once 15 epochs with the latter learning rate were reached, the learning rate was reset to 0.001 and the loop was continued. We also tried FCN-8s and Mobilenet V3, so far UNet was the best. The accuracy is about 65%. Figure 3 shows the results of our thermal AI, the AI reveals the potiential thermal bridges on the building and the images with RGB data are further used in 3D reconstruction algorithm.

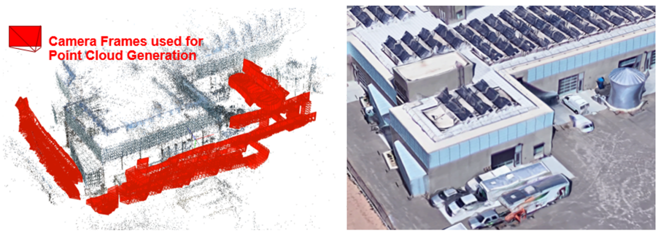
B. GPR AI experiment

The AI training dataset is generated by scanning a plywood glued with six pieces of paper towel of varying moisture content which can simulate a wall with non-normal moisture condition. Over the plywood was various construction materials like batt insulation, rigid foam insulation, metal and wood stud, more plywood, brick, concrete, and combinations of these. As the figure 3 shows, the GPR AI has the ability to distinguish areas with moisture when



(a) (b) (c) (d) (e) (f)

Fig. 3: Thermal AI and GPR AI results: (a) Thermal AI Demonstration; (b) Thermal AI Training results; (c) Thermal AI Validation results; (d) GPR AI Demonstration; (e) GPR AI Training results; (f) GPR AI Validation results



(a) (b)

Fig. 4: Comparision between the (a) color image point cloud and (b) Google map

radar module is assembled on the UAS. The output of the modified GPR AI is a H x W image of size 1 x length of the scan. Areas that are non-dry have have a value of 1 and 0 otherwise. Based on this, the AI has an accuracy of 95% and only fails at the edges of generated moisture.

C. 3D Reconstruction Algorithm experiment

We evaluate our 3D reconstruction algorithm by collecting data from Trades and Advanced Technology Center, Santa Fe Community College. The foot print of the building is about 31,000 ft^2 and the height is 36 ft.The total surface scanned is about 8,900 ft^2 and the total flight time is 37 minutes. We planned a zig-zag flight path around the outer wall of the building with a offset of 5m. Figure 4 shows the comparison between color image point cloud and google map where the red blocks are the camera frames. On each corner, the UAS rotates by yaw axis to collect the feature points on both sides of the corner of building. The algorithm has successfully generated the 3D point cloud and the estimations are reduced by bundle adjustment, making it more consistent.

V. Conclusion

In this paper, we proposed a system of robots and AI for building envelope inspections called EASEEbot. In current practice, inspections are costly, destructive and inspectors have to deal with safety and accessibility issues. EASEEbot addresses these issues by utilizing a UAS, a GPR, a retrofit Robo-dog, and AI algorithms which can significantly reduce the inspection costs, risks of working at heights, and inaccessibility issues. During the non-destructive data collection and analysis phase, EASEEbot uses the UAS in flight mode to collect the thermal & RGB images and wall climber mode to collect GPR scans. Further, the thermal AI identifies thermal defects while the GPR AI finds hidden moisture content on building envelopes. To eliminate safety risks, EASEEbot employs an omnidirectional obstacle avoiding system on UAS flight mode and a tether system on UAS wall climber mode. Moreover, EASEEbot offers a retrofit Robo-dog to help with the building defect point visualization to increase the productivity of the retrofit process. In the future, we plan to showcase an autonomous robot with a GPR unit to scan horizontal and slightly inclined surfaces such as a roof, train the GPR AI to detect and predict the corrosion condition of masonry ties in masonry walls, and improve the UAS wall climber motion on rough building façades.

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