Large-scale Google Street View Images for Urban Change Detection

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***Abstract*—Urbanization has entered a new phase characterized by urban changes occurring at a micro-scale and "under the roof", as opposed to external modifications. These changes, known as urban retrofitting, involve the incorporation of novel technologies or features into pre-existing systems to promote sustainability. Given the limitations of remote sensing images in identifying such urban changes, novel tools need to be developed for detecting urban retrofitting. In this study, we first build a pipeline to collect large-scale time-series urban street view images from Google Street View in Mecklenburg County, North Carolina. And we examine the feasibility of utilizing the acquired dataset to detect diverse forms of urban retrofitting, including re-building, re-greening and re-capital.**

Keywords*—*Urban Change Detection, Street View, Large-scale Spatial Data, Urban Planning component

I. INTRODUCTION

Urban change detection is critical to policymakers and urban planners seeking to understand urban environments and formulate policies for future urban development. Over the past few decades, the detection of urban changes has primarily relied on remote sensing images [1]. As fine spatial resolution remote sensing data products have become increasingly accessible, urban changes such as building construction [2], vegetation or greenspace changes [3], and water body detection [4] can be effectively identified. However, urbanization has recently transitioned into a new phase characterized by a greater prevalence of changes occurring at micro-scale, and "under the roof" rather than outer building structure. And those changes known as urban retrofitting, involve integrating new technologies or features into existing systems to promote sustainability [5]. Such modifications often do not entail substantial alterations to the physical infrastructure of buildings [6]. Consequently, remote sensing is inadequate for detecting urban retrofitting, especially for urban re-capital, which falls within the domain of urban retrofitting and urban re-development. This process often involves adjustments in urban building functionality aimed at enhancing land value and promoting sustainability, such as the conversion from commercial to residential use, without accompanying modifications to the physical structure of buildings. Therefore, remote sensing data is not suitable for detecting these changes effectively. Given their importance, it is essential to develop novel detection methods specifically designed to address these latest urban changes as retrofitting, which are difficult to capture using conventional remote sensing approaches.

The wide availability of street view data, such as Google Street View images, has presented a significant opportunity to address the aforementioned challenge. Street view images, when combined with computer vision techniques and machine learning models, have been effectively utilized for detecting instances of building changes [7], identifying building improvements [8], and analyzing urban growth patterns [9]. In this context, our research objective is to develop a machine learning-based pre-trained foundation model capable of detecting various types of urban changes and their timing using a time-series of street view images [10]. To accomplish this goal, large-scale urban street view images need to be collected for the purpose of training the machine learning model. We have developed a workflow capability to automatically collect extensive street view images from Google Street View. We then apply this capability to Mecklenburg County, North Carolina, where the city of Charlotte is located, to generate a comprehensive set of time-series street view images. Additionally, we examine distinct categories of urban changes and urban retrofitting, and utilize the gathered dataset to identify diverse forms of urban transformations occurring within Mecklenburg County.

II. STUDY AREA AND DATA

Charlotte has experienced substantial growth in the past few decades, ranking among the fastest growing metropolitan areas in the United States [11]. According to the 2020 census, Mecklenburg County, where Charlotte is situated, houses over 1.1 million residents, making it the second-most populous county in North Carolina, following Wake County. With a population increase of 60.4% between 2000 and 2020, Mecklenburg County has undergone rapid urbanization, resulting in significant urban changes. This case study needs to collect a comprehensive dataset of Google Street Images, including historical images, to analyze various types of urban changes occurring in Mecklenburg County. To meet this need, we began by downloading the shapefile of Mecklenburg County from the Charlotte Data Portal (https://data.charlottenc.gov/), utilizing the version updated on January 5, 2022.

The data collection workflow comprises two algorithms, namely Algorithm 1 (Capture Street View) and Algorithm 2 (Batch Data Collection). Algorithm 1 focuses on collecting time-series street view images at a particular location, while Algorithm 2 handles large-scale data collection. Specifically, Algorithm 1 takes in longitude and latitude as input data. By incorporating the heading (camera direction) and pitch (up/down angle of the street view), we construct a Uniform Resource Locator (URL) that directs to the corresponding Google Street View. Within a short loading timeframe, we capture a screenshot of the street view image. Subsequently, we iterate the process by clicking the next date button to gather screenshots of all the historical images available for that specific location and point-of-view (POV) combination, until all historic images have been exhausted.

```
Algorithm 1: Capture Street View
Data: lon, lat
driver ← start_web_driver();
pitch ← 20;
while next_date do
    while heading ← [0, 90, 180, 270] do
        url ← create_url(lon, lat, heading, pitch);
        driver.get(url);
        sleep(gap_time);
        screenshot ← take_screenshot();
        save_screenshot(screenshot);
        url = next_date(url) ;
    end
end
```

Algorithm 1. Capture Street View

Algorithm 2 utilizes the Mecklenburg County shapefile to generate a large-scale dataset encompassing the entire county. To ensure systematic data collection, we employ the census tract block group as the spatial unit. The block group represents the smallest geographical unit for which data is published by the census bureau. This selection is based on the fact that block groups generally consist of a relatively consistent population size ranging from 600 to 3,000 individuals [12]. To gather data for all 555 block groups in Mecklenburg County, we employ a random sampling technique, selecting 10 pairs of coordinates within each block group. We then attempt to retrieve Street View images by utilizing the Capture Street View function defined in Algorithm 1.

```
Algorithm 2: Batch Data Collection
Data: Census_Tract_Block_Groups
while block_group ∈ Census_Tract_Block_Groups do
    shp ← get_geometry(block_group);
    while i ← range(0, 10) do
        lon, lat ← get_random_points(shp);
        Capture_Street_View(lon, lat);
    end
end
```

Algorithm 2. Batch Data Collection

Our data collection effort resulted in the accumulation of 620 GB of street view data, comprising a total of 95,113 images. Among these, we obtained a dataset containing 13,115 sets of time-series street view images, which encompass various combinations of locations and POV parameters. It is important to note that the number of time-series images can vary depending on the selected location, with more historical images typically observed in closer proximity to downtown Charlotte. On average, each location in our dataset contains 7.25 images, while the maximum number of historical images obtained for a single location reaches 22. The distribution of the collected street view image locations is illustrated in Figure 1, which highlights a total of 3,280 valid locations.

Fig. 1. Distribution of Data Collection Locations

III. URBAN CHANGE DETECTION

This research aims to analyze the collected street view data to examine various urban changes and urban retrofitting, with a specific focus on three significant types of sustainability-oriented urban transformations: 1) Re-building, which entails the intensification of urban space utilization, including the construction of new buildings and the adaptive reuse of vacant commercial buildings; 2) Re-greening, which involves urban improvement aimed at creating resilient, beautiful, durable, culturally significant urban environments that meet high standards of environmental performance both in the public spaces and the buildings; and 3) Re-capital, which involves adjustments in urban building functionality aimed at enhancing land value and promoting sustainability. These types of changes have been identified as significant in the context of sustainable urban development [5]. In addition, many urban changes that fall into these categories often happen at micro-scale and "under the roof", which can be hard to detect with remote sensing images. Our particular focus lies on street view images that facilitate the identification of these urban transformations, which often prove elusive when relying solely on remote sensing imagery.

By utilizing the street view images, we were able to determine not only whether urban changes have occurred in a specific area but also the type of urban changes that have taken place. Furthermore, we gain insights into the timing of these urban transformations, enabling a comprehensive understanding of when these changes occurred.

A. Urban Re-building

Figure 2 illustrates an example of the collected street view data used for detecting urban re-building. The analysis focuses on a specific configuration with latitude at 35.228 and longitude at -80.844. In this configuration, a total of 12 time-series images were collected spanning from February 2008 to March 2021. The location is situated in downtown Charlotte at the intersection of W Trade St and N Church St.

The analysis of Figure 2 reveals evidence of urban re-building. From February 2008 to March 2018, there was minimal construction activity observed. However, urban reconstruction occurred between March 2018 and April 2019 when the Grand Bohemian Hotel Charlotte was built. Based on Figure 2, the construction process continued in April 2019 and March 2020 for interior decoration, as evident from the lower portion of the street view images. Although the construction of the building between March 2018 and April 2019 may be discernible using high-resolution remote sensing images, the interior decoration detected with street view images, which is a part of the urban reconstruction and urban re-building, is difficult to identify through remote sensing images.

Fig. 2. Urban Re-building

B. Urban Re-greening

An example of urban re-greening is found in the dataset at 936 South Blvd, Charlotte, NC. with a specific configuration of latitude at 35.219, longitude at -80.848 at 936 South Blvd, Charlotte, NC. Figure 3 presents the visual evidence of re-greening in this area. Initially, between October 2007 and September 2011, re-greening is observed on the roadside. Subsequently, between March 2017 and April 2019, a small greenbelt is established in the middle of the two-way traffic road. While large-scale urban re-greening projects, such as the establishment of new parks, are typically identifiable through the use of Normalized Difference Vegetation Index (NDVI) derived from remote sensing images, micro-scale urban re-greening initiatives, such as the greenway constructed in the middle of the road (Figure 3) cannot be effectively detected even with the highest resolution remote sensing imagery. In this context, street view images, offering enhanced levels of detail, hold potential value, particularly for detecting micro-scale urban changes.

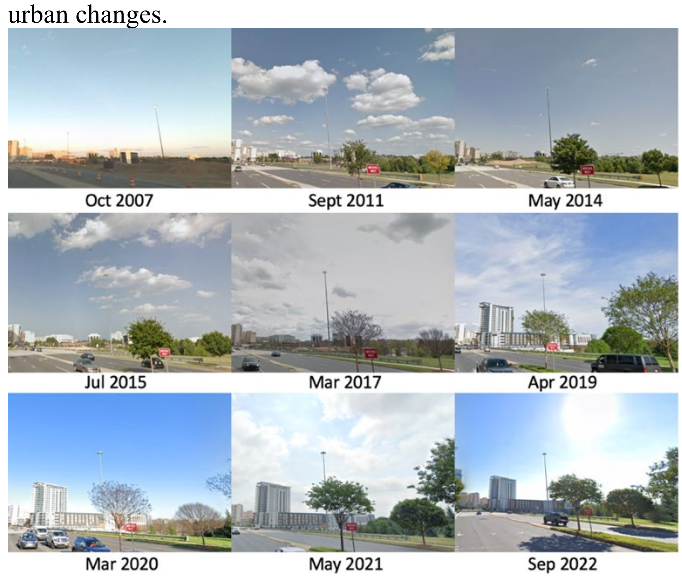

Fig. 3. Urban Re-greening

C. Urban Re-capital

Figure 4 illustrates an instance of urban re-capital observed in the North Davidson (NoDa) area, which has experienced rapid urban retrofitting since 2000. From February 2008 to March 2020, the building served as Behailu Academy, an art-based after-school program for youths. However, in August 2021, while Behailu Academy still occupies the right section of the building, the other portion has been transformed into an art market offering market space, a bar, and provisions. Although minimal changes are apparent in the building's exterior, the functional transformation from March 2000 to August 2021, characterized by increased building density and urban re-capital. And such changes occurring "under the roof" can be effectively detected utilizing street view images, while remote sensing images lack the capability to capture them.

Fig. 4. Urban Re-capital

IV. Conclusion

In summary, this research has generated a comprehensive dataset of Google Street View images that can be utilized to detect urban changes, particularly for urban retrofitting, which often occurs at a micro-scale level and "under the roof." In the specific case study conducted in Mecklenburg County, we introduced our scalable data collection workflow, resulting in a dataset comprising 95,113 images and 13,115 sets of time-series street view images. Through a preliminary analysis, we demonstrated the effectiveness of this dataset in detecting various urban changes, including re-building, re-greening, and re-capital. Furthermore, we showed that street view images offer a valuable means of effectively identifying numerous urban retrofitting changes. In contrast, remote sensing images may lack the capability to detect such changes with comparable efficacy.

In the future, we plan to develop a pre-trained foundation model to automate the process of urban change detection. Using any series or pairs of historical street view images captured at the same locations, together with related environmental and population data, our pre-trained model aims to address three fundamental questions: 1) whether there are urban changes happening; 2) what types of urban changes happened and; 3) when the urban changes take place.

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