Towards a Computational Approach to Quantify Human Experience in Urban Design: A Data Collection Platform

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Abstract –

Design features that form urban settings such as greenery, height of buildings, and variation in the building façade (materials, color, and proportion) are known to have effects on how people experience environments. As the urban population grows and shifts to urban settings for living (e.g., 82% of people live in cities in the US), understanding the impact of urban environments on human experience becomes more essential. Previous studies to capture human experience in urban settings have been limited due to the labor-intensive and manual process of data collection (i.e., field surveys). Due to limited quantified data on urban design features, previous methodologies were constrained to a few neighborhoods, hence lacked generalizability across regions. Advancements in technologies such as GIS, computer vision, and data-driven methodologies and accessibility to large image sets on urban settings provide opportunities to eliminate the labor-intensive process of data collection. With the help of technologies, it is possible to quantify how people experience cities. This study leverages such advancements and aims to develop an automated approach for quantifying human experience toward built environments regarding their restorative impact on citizens. Towards this aim, within the context of this paper, we provide the details of a web-based crowdsourcing platform developed for the data collection at urban scale. We combine Geographic Information System (GIS), Google Street View (GSV), and JavaScript libraries to build the platform to capture the responses of participants on the restorative impact of the environments displayed to them as images. Based on the geolocation information obtained from GIS, we collected high resolution 360˚ GSV images within New York City (NYC) and used them to collect responses of citizens on structured questions tailored to the scope of the study. The crowdsourcing platform enables participants to evaluate the overall restorative impact of environments given in a 360˚ image, and to specify areas and design features influencing their evaluation. To quantify the influential design features on responses, we use semantic segmentation, and perform statistical analysis on the dataset to examine the impact of each urban design feature on the overall restorative impact. The approach will be presented for researchers to integrate GIS, Google API, and libraries to pull massive urban data for research study necessitating a good representation of the built environment as inputs. The outcomes will guide practitioners in urban redevelopment projects about urban design features that are influential.

Keywords –

Urban design; Restorative environments; Computer vision; Semantic Segmentation; Crowdsourcing; GIS; Google Street View

1 Introduction

The indoor and outdoor built environment has a strong association with restorativeness, which directly impacts mental fatigue, stress indicators, and quality of life of individuals [1-5]. As the urban population grows (82% of Northern American people are living in cities), the stress level of the urban residents has increased because of reduced space and overcrowding accompanied with urbanization [6]. With the aim to improve the quality of life, many researchers have been focusing on studying the impact of the built environment on human perception, including the restorativeness of the environment on people [7-9]. Various studies under this umbrella evaluated the relationship between the built environment and people's experience (e.g., preference, feeling of safety, stress/anxiety) and behavioral changes (e.g., reduction/increase in physical activities) in urban settings [1-6,10]. Their studies evaluate the built environment at micro and macro scales, including understanding the effect of various urban design elements, such as buildings, streets, and urban design blend as a whole. Majority of such empirical studies utilized Geographic Information System as a tool to quantify properties of such elements in the built environment (e.g., urban density, building height), resulting in many street level design elements (such as the presence of street furniture, type of building façade) being omitted due to the hardship of data collection and representation format in existing data sources, mostly being shapefiles. In order to reflect street level elements as impacting factors on human experience, more recently, few studies have utilized urban street imagery and machine learning algorithm. These studies used urban street images that are prelabeled by people indicating how they feel about the environment in the images to predict people's perception (e.g., safety, excitement) about a given environment [11-15]. However, previous studies used non-panoramic and low-resolution images, which lacked rich visual information to give realistic experience of streets. In addition, what lacked in those approaches are the assessment of individual contributors of the type and amount of urban design elements on the resulting influence. Such information is essential for urban designers/practitioners to shape the urban settings with clear knowledge on how they will positively influence people's experience in an area.

Hence, in this work, we propose the details of a data collection platform that will enable (a) capturing rich geometric and visual information from multiple perspectives in a given area, and (b) correlating the overall experience of people in that area with the type and quantified properties of urban design elements that make up that area.

2 Literature review

This study is at the intersection of (a) previous studies that evaluated urban design elements on their restorative impacts on people, (b) metrics defined for measuring restorative capability of an environment, (c) data collection methods to measure impact of urban settings on people, and (d) contemporary and large image sets from urban settings.

2.1 Urban design elements and their impact on human experience

This work focuses on the restorativeness impact of the built environment on human experience, which is defined as the potential to recover and increase cognitive, physical, and mental capacity of people [27,34]. The effects of restorative environments on physical, social, and mental well-being has been examined extensively by studies in environmental psychology domain [3, 33].

Kaplan & Kaplan (1989) established the attention restoration theory and the value of nature on psychological restoration [27]. Based on that, studies in environmental psychology domain have empirically proved that not only the natural environment but also the presence of certain elements in the built environment have restorativeness effect on people. Examples of these urban design elements are provided in Table 1. Due to the high population density of cities, this potential of restorative environments in urban settings is significant.

Table 1. Urban design elements that were studied for restorative impact of the built environment

	Urban design elements	Reference
Built environ ment	Height of buildings	[4,5,28]
	Presence of socialization places such as cafés and restaurants	[25,26]
	Width of streets	[28]
	Visual complexity (e.g., the number of signages, dis/continuity of building façade style)	[23]
	Presence of landmarks and historical buildings	[24,27]
Natural environ-ment	Presence and amount of water bodies around	[23,25]
	Presence and amount of vegetation (e.g., trees, flowers, plants) around	[4,5,16-18]

2.2 Metrics defined for measuring restorative capability of an environment

One of the first studies that aim at measuring restorative impact of an environment is by Hartig et al. (1997). Perceived Restorativeness Scale (PRS) suggested by that study has been used to capture restorative quality of environments in environmental psychology studies. PRS was designed to measure the restorative quality of environments by capturing four psychological aspects - which are Being-away (being away from daily concerns), Fascination (capacity to drag people's attention), Coherence (clear order of the physical arrangement of design elements), and Compatibility (match between people's goals and availability of required activity in the place). The original version of PRS composes of 11 scale (0-10) and 26 questions. After Hartig et al. (1997) suggested PRS, several researches have made efforts to make shorter versions of PRS questionnaire and prove the usability of new versions of questionnaires [5,11,21,22]. In this study, to adopt a user-friendly and a shorter version, we adopted PRS questionnaires as used in Lindal & Hartig (2013) to capture being-away and fascination of built environments in urban settings. Due to characteristics of an online crowdsourcing platform, the shorter version of questionnaire is more appropriate for the participants' convenience and the reliability of the collected information.

2.3 Data collection methods utilized in literature

Previous studies are mainly empirical studies that aim to define the urban design elements that affect the restorative impact of a neighborhood. Such studies examine the direct and indirect effects of physical urban design elements (e.g., building height, presence of greenery and vegetation, bench) on streets on restorativeness, measured through a combination of metrics such as the feeling of openness, being away, fascination, compatibility, and complexity [4,16-18]. The data collection efforts that provide the required inputs for these studies can be mainly grouped under three categories: (1) field experiments, which include taking trips to areas of interest and conducting interviews with participants [19,20]; (2) image auditing, which includes using static street images with varying context (e.g., commercial area vs. historical place, residential area vs. parks and recreational areas) and comparing people's responses [21,24]; and (3) 3D modeling, which includes generating digital replica of an urban location with controlled objects in a scene and asking questions to participants regarding their perception of the area [4,16].

Each one of the described categories has specific limitations: field experiments are labor intensive, image auditing is manual for quantitative analysis of each urban design element on a scene, and 3D modeling is time-consuming to get realistic representation in virtual worlds. Besides the limitations that are specific to each category, they share a common limitation that hinders the extension and generalization of research outcomes, because of the fact that they could only focus on a specific urban area in these labor-intensive data collection processes. Hence, to alleviate the limitations in the existing data collection processes and enable collection of massive and rich data on urban settings, we describe a data collection platform that can merge several data sources, slice, and extract geometric and location information of areas with rich contextual data.

2.4 Contemporary and large image datasets that are generated to measure human experience in urban settings

A few recent studies focused on understanding human perception on the aesthetic preferences of people in urban settings using images and data-driven methods [29-31]. Although these studies differ in the urban evaluations, they are worth mentioning here because of the large datasets generated for similar purposes. Being one of them, the Aesthetic Visual Analysis (AVA) dataset has 250,000 images with semantic annotation (e.g., cityscape, landscape, architecture, etc. already labeled) and ratings of people on the images about how aesthetic they find [29]. Using the AVA dataset, some of the studies examined the possibility of machines mimicking human perception toward the selection of places (represented as images) with high aesthetic appeals [30,31]. Beyond this dataset, a few research studies have generated image sets on human perception in street level urban environments [11-15,32]. Place Pulse project by MIT Media Lab collected human perception regarding safety, wealth, boring, beauty, depressing, and livability using 100,000 images from 56 cities by comparing two street images and selecting better image in terms of being safer, wealthier, less boring, more beautiful, less depressing, and more livable [11,12]. The image ratings are through pairwise comparison of two static images, which show the place only from one viewpoint and without disaggregating the images into influential urban design elements on human perception The data platform presented in this paper eliminates these limitations by enabling (a) capturing high-resolution 360˚ panorama images of locations of interests, and (b) annotations on images for defining the influential objects in assigned ratings by participants.

The results of previous studies that utilize such image datasets to predict human perception indicate that visual representations captured in images are reflective of human perception and are promising to study urban design through leveraging image datasets. Previous studies also provide a point of departure about the strong indication that a machine can mimic human perception in an urban environment if presented with structured and large data. With the overall aim to have an empirical study on quantifying human restorativeness on urban environments, this paper provides the data collection platform developed to provide the required input of well-structured and large datasets for such studies. The structure of data is maintained through disaggregation of captured images to primitive urban design elements and quantifying their influence on the overall human experience.

3 Urban-scale data collection platform

In this section, we provide the details of the platform by introducing the major components of this platform and how they function and interact with each other. Major components of the platform are explained based on their roles in forming the image database (part 1 in Figure 1) and in capturing participants input in the crowdsourcing phase of the data collection (part 2 in Figure 1).

3.1 Overview

An overview of this platform is provided in Figure 1. First, the urban image database for images from areas of interests should be captured, which includes Geographic

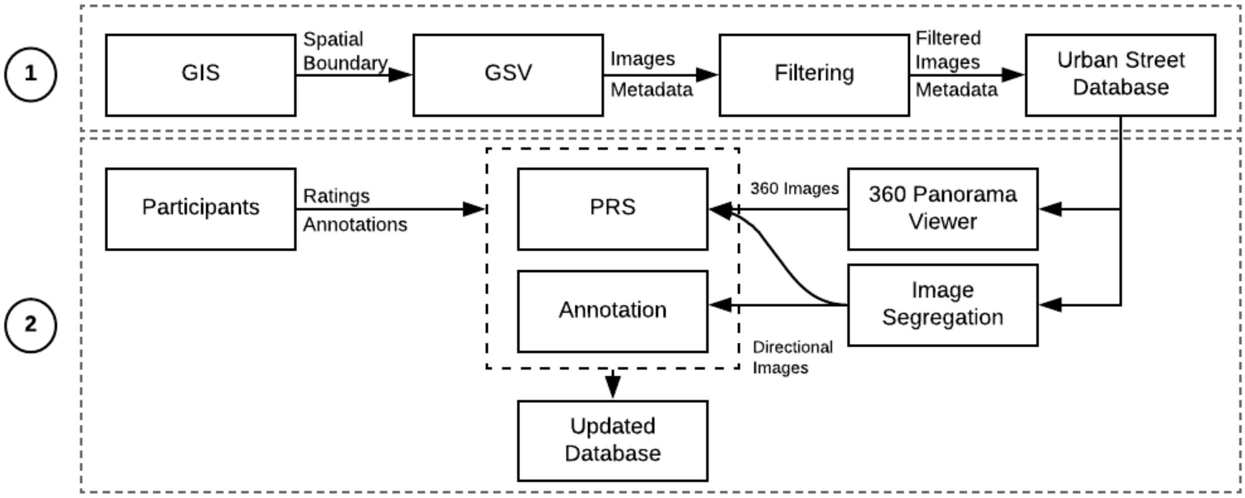

Figure 1. Components of the data collection platform and their interactions.

Information Systems (GIS) and Google Street View (GSV) APIs. The images are stored for locations represented with global latitude and longitude information of a specific location in Google's database and retrieved by a point by point request through Google API. Therefore, to request images through Google API, we need to (1) set the spatial boundary of interest using GIS, (2) generate a large number of points within the boundary in GIS, and (3) request the images and metadata (i.e., panoID, geographic coordinate) through Google API. During this request, all types of images from GSV including the ones about indoor environments are also retrieved. Therefore, a filtering component has been integrated in the platform that use semantic segmentation and unsupervised learning to eliminate images that are irrelevant (as detailed in section 3.4).

The images that stand out after the filtering are stored in our database and ready for use in part 2 of the platform (labeled with #2 in Figure 1). This part deals with capturing and storing response of citizens, who participate in the crowdsourcing based data collection. The data to be collected includes the ratings of people on restorative impact of the environment displayed on a set of randomly assigned 360˚ images and the associated unidirectional images (i.e., an image from front, back, left, right of a selected field of view) along with the annotations on images that define sections that were influential in participant ratings (see details in section 3.3). Ratings are captured through a 1-5 Likert on the perceived restorativeness scale (PRS) (detailed in section 2.2). In summary, the data collection platform enables to capture: (1) GSV image, (2) segmentation output of the image, (3) crowdsourced ratings on 360˚ and each directional image, and (4) annotations of influential urban design elements present in an image (Figure 2).

The following subsections provide further details of these components and their functions over the example implementation in New York City.

3.2 Populating the Urban Street Image Database

GSV is an open data source that provides street imagery and its metadata, which can be requested by a panoID or geographic coordinate. In the platform presented here, 360˚ panorama images are captured from Google Street View (GSV) in equirectangular projection, which is a 360˚ panorama image representation format providing a 360˚ horizontally and 180˚ vertically stitched image (Figure 4). Extracting the related images for a

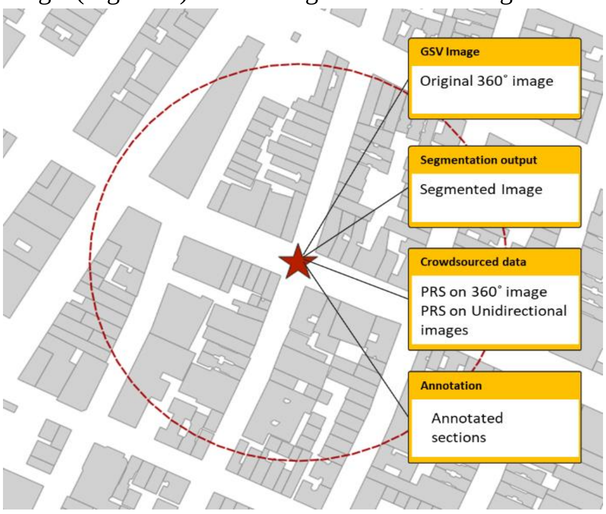

Figure 2. Data captured and stored through the platform for one image.

neighborhood of interest, first a spatial boundary is defined in GIS. An example boundary (near Washington Square Park, NYC) is provided in Figure 3. We generate a number of points in GIS (represented as latitude and longitude) within this boundary and request GSV images and their metadata for each point generated. As a result, generated points within the specified boundary are matched with available GSV data as shown in Figure 3. As part of the metadata, there is "panoID" which is the unique key representing a street view image. Using "panoID", 360˚ panorama GSV images are retrieved in this platform.

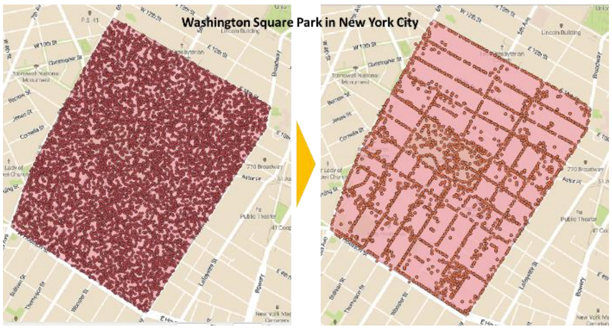

Figure 3. Illustration of a spatial boundary selection and mapping of GSV metadata within the boundary. Left: generated points by GIS; Right: obtained images.

Using this process, it is possible to populate a large image dataset for a neighborhood of interest without the need for time consuming manual image collection. The image resolution we obtained is 8192 × 4096, which is the same quality of 4K 360˚ camera and 4K content in VR device, surpassing the problems in previous data collection efforts resulting in low resolution images (640x640) and lack of visual details. For testing of this platform, we captured 2,628 images from NYC Washington Square Park area.

3.3 Projecting images and annotation

Equirectangular image is a popular format to store and convey 360˚ panorama images. However, the image is not intuitive to human perspective because it is projected as a single flat image with 360˚ horizontal and 180˚ vertical coordinate in the image (Figure 4). Therefore, to use the equirectangular image in the platform, the image needs to be converted to a perspective projection image.

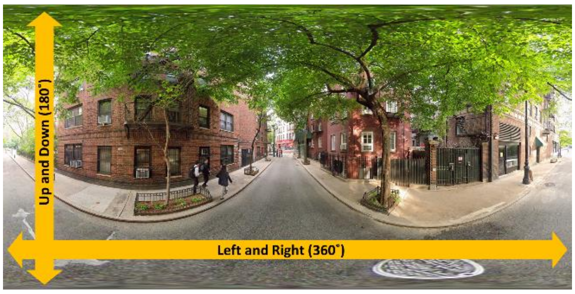

Figure 4. Equirectangular image

Firstly, to capture entire human experience in the place at the first page, we used a 360˚ panorama viewer. We used open source panorama viewer Pannellum, which is built using web programming language (Figure 5). Next, we extracted unidirectional images from equirectangular images (Figure 6). The selected field of view are looking front, right, left, back and up along the street.

Figure 5. Equirectangular image projected in a 360˚ panorama viewer.

Figure 6. Unidirectional images (Front, left, up, right, bottom along the street) extracted from the equirectangular image shown in Figure 5.

To facilitate capturing parts of an image that were influential to a participant's ratings on restorative impact of that image, we set HTML canvas that allow users to draw rectangles on sections in images (Figure 7). The rectangular shapes on canvas are stored as images during the data collection process, which will be segmented further in the data analysis phase for quantifying urban design elements.

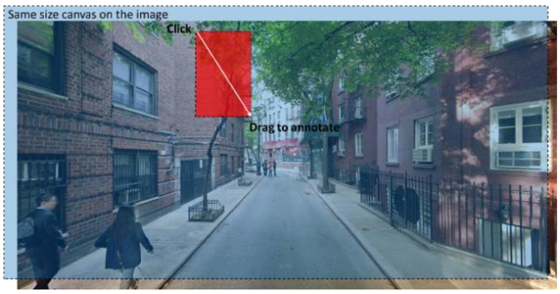

Figure 7. Annotation capability in the platform.

3.4 Filtering out irrelevant images

The automated population of images from GSV in a spatial boundary could result in extracting images that are stored in GSV but not representing street views. To eliminate such irrelevant images from the image database, this data collection platform has a filtering component that utilize semantic segmentation and unsupervised learning to classify indoor and outdoor images. During the initial step of populating the urban image dataset, points generated could match to images that are representing indoor environments. In order to exclude the images related to indoor environments, we used semantic segmentation and unsupervised learning. Semantic segmentation enables us to parse images and assign a class label (i.e., flower, tree, building, car) by pixel level and unsupervised learning facilitates clustering based on the segmentation output (objects in the image). Since the indoor environment has distinct object compositions from outdoors, one of the clusters represents the indoor images. For semantic segmentation, we utilized the HRNetV2 model, which is a neural network based model developed by Sun et al. (2019) as a segmentation model [35]. Since the objects appearing in indoor and outdoor images are distinguished (i.e., indoor: chairs, floor, ceiling, refrigerator, as shown in Figure 8; outdoor: cars, trees, sky, buildings, as shown in Figure 9), the unsupervised learning algorithm can learn the difference between indoor and outdoor images based on the information from the output of semantic segmentation of the image without label. Figure 8 and 9 show segmentation results for images captured indoors and outdoors, respectively.

Figure 8. Sematic segmentation of an image from indoors. Top: original image; Bottom: segmented image, where each colour represents a different category of objects.

The performance of the filtering process has been tested using the images captured in Washington Square Park boundary as a testbed. For the testbed we generated,

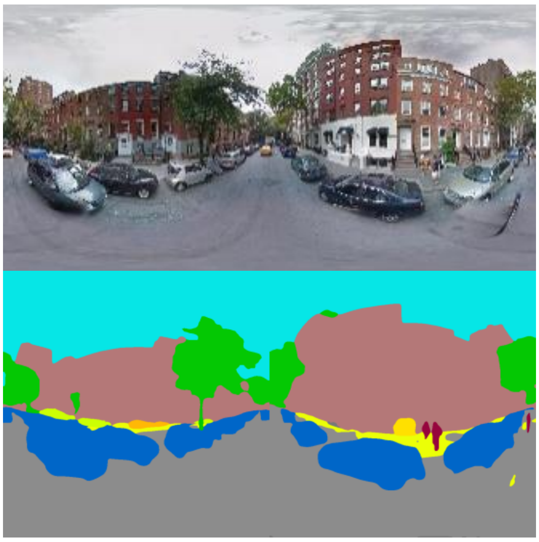

Figure 9. Semantic segmentation of an image from outdoors. Top: Original image; Bottom: Segmented image, where each color represents a different group of objects.

We eliminated 406 images from the original urban street image set from Washington Square Park. The overall accuracy of the model to classify indoor/outdoor images was 99.23% and the only error was on Type I (i.e., outdoor predicted as indoor) as 5% (Table 2).

Table 2. Accuracy of indoor/outdoor classification model.

Actual class / Prediction	**Indoor**	**Outdoor**
Indoor	**386**	20
Outdoor	0	**2,222**
Accuracy	**99.23%**	

3.5 Crowdsourcing to capture citizen ratings

PRS to measure restorativeness impact of a location and 360˚ panorama GSV images were integrated and implemented as part of a questionnaire in a crowdsourcing platform to capture the restorative quality of places in urban settings. The crowdsourcing platform was developed by utilizing JavaScript and SurveyJS for generating the survey forms and integrates to the urban street database generated. The questionnaire composes of six pages, where each page has the same PRS questions (Figure 10). A participant will be given a 360˚ panorama image (same as a GSV in Google Maps) on the first page, and the rest of the pages will show the unidirectional images (along the street: front, right, left, back, up). The reason for collecting responses for each disaggregated image is since the PRS ratings of the 360˚ panorama image includes contributions of each disaggregated image. Additionally, in each unidirectional view of the location (e.g., front), participants are asked to select areas that were influential in their ratings of that location's restorative capacity as annotations on the image.

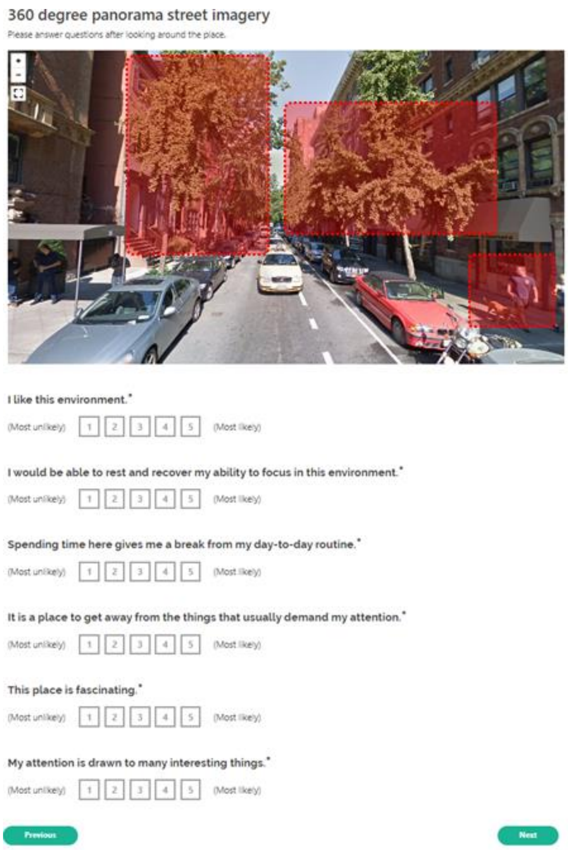

Figure 10. Crowdsourcing part of the platform.

This information is captured and used to update the images stored in the filtered database. Figure 11 shows examples of images stored in the urban image dataset through the utilization of the platform.

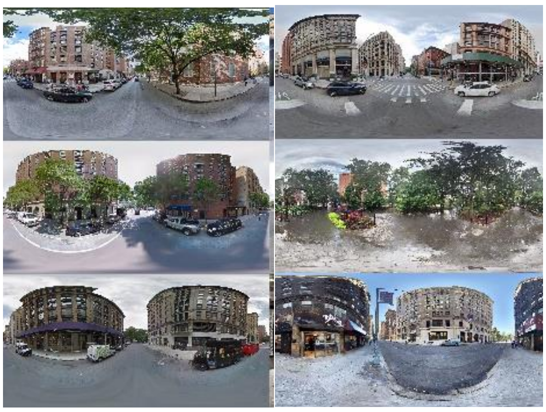

Figure 11. Examples of collected 360˚ panorama images

4 Conclusion and Future Work

We developed a data collection platform that integrates GIS, GSV, and a crowdsourcing module to enable capturing of massive and high-resolution urban scale image sets that are rich in visual information. The platform also enables marking urban design elements present in images and relating them to citizen ratings captured through the crowdsourcing component. We implemented this platform and developed measurement tools to capture a sense of restorativeness towards urban street images. The platform uses semantic segmentation and unsupervised learning to classify images to exclude indoor images retrieved from GSV.

The collected data is anticipated to be used to identify the urban street elements affecting perceived restorativeness as a future work. Finally, we expect that this platform will be utilized in other interdisciplinary studies since the database and platform have the potential to be extended to capture other aspects relevant to urban studies possibly expanding with other GIS data such as census data, land use data, and building data as needed.

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