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## 穿戴式相机在研究个体行为 与建成环境关系中的应用

# APPLICATION OF WEARABLE CAMERAS IN STUDYING INDIVIDUAL BEHAVIORS IN BUILT ENVIRONMENTS

### 1 研究背景

当前，城市规划领域中对微观尺度的居民需求与空间品质的关注度不断提升，城市设计与更新也更加强调个体空间的使用与体验。而在研究人体行为与城市设计的关系方面，国内外学界均已有一定积累。自20世纪80年代起，芦原义信<sup>[1]</sup>、克莱尔·库珀·马库斯<sup>[2]</sup>、扬·盖尔<sup>[3]</sup>等人陆续奠定了行为与场所空间使用之间关系的研究基础，劳伦斯·D·弗兰克等<sup>[4]</sup>及安妮·瓦尔内兹·穆东等<sup>[5]</sup>则基于实证研究，探索

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#### 张昭希

清华大学建筑学院研究助理；同济大学建筑学硕士

#### 龙瀛\*

清华大学建筑学院特别研究员、博士生导师

\*通讯作者

地址：北京市清华大学建筑学院

邮编：100084

邮箱：ylong@tsinghua.edu.cn

#### 摘要

随着第四次工业革命的到来，人们开始不断探索新技术和新设备在研究个体行为与城市设计关系上的潜力。穿戴式相机的出现为监测个体在空间中的行为、形成个体“生命日志”提供了更多可能。本文以个体佩戴者为单位，探究穿戴式相机在研究个体行为与建成环境关系中的应用。研究通过人工识别、调用计算机视觉分析应用程序编程接口、利用Matlab进行色彩识别三种方式，对佩戴者在一周时间内收集到的8 598张照片进行了图像识别，并对比了三种方法的优劣势。随后，基于准确性较高的人工识别结果，研究对个体行为特征、时间分配、路径转移、场所事件等方面展开分析。研究表明，穿戴式相机采集的图片大数据库蕴含丰富的个体行为与时空信息，可以有效描述个体在空间中的行为特征，对研究个体行为与建成环境之间的关系具有重要意义。

#### 关键词

可穿戴设备；时空间行为；生命日志；数字自我；图片大数据

#### ZHANG Zhaoxi

Research Assistant at School of Architecture, Tsinghua University; Master in Architecture, Tongji University

#### LONG Ying

Special Researcher and Doctoral Supervisor at School of Architecture, Tsinghua University

#### ABSTRACT

With the advent of the Fourth Industrial Revolution, people have begun to explore the potential for new technologies and new devices in studying the relationship between human behavior and urban design. The emergence of wearable cameras offers more possibilities for monitoring individual behavior in built environments as a kind of "lifelog." This article explores the applications of wearable cameras in studying the relationship between individual behavior and built environments. Using manual image identification, image recognition with Computer Vision Application Programming Interface (API), and color calculation in Matlab, this study analyzed 8,598 photos recording the volunteer's behaviors and activities during a week. Based on high-accuracy manual image identification results, the research analyzed the volunteer's behavior, time use, movement path, and experiencing scenes. The study showed that the big data base of images collected by the wearable cameras contained rich individual activities and spatiotemporal information that could be used to effectively describe the individual behavior in space and further contribute to the study of the relationship between individual behaviors and built environments.

#### KEY WORDS

Wearable Device; Spatiotemporal Behavior; Lifelog; Quantified Self; Big Data of Pictures

编辑 汪默英 余依爽 翻译 张健 萨拉·雅各布斯

EDITED BY WANG Moying SHE Yishuang TRANSLATED BY Angus ZHANG Sara JACOBS

了城市街区环境要素对人群活动的影响；徐磊青<sup>[6]</sup>、潘海啸<sup>[7]</sup>、陈泳<sup>[8]</sup>等中国学者则聚焦于人在环境中的行为变化，通过观察、问卷、访谈等方式记录了人们出行和接触环境的情况，分析了城市环境对人们行为的影响。尽管目前此类研究已经取得一定成果，但关注个体使用者在城市空间中行为特征的研究仍然较少——受人力和时间成本限制，研究者难以客观、长期、连续地对某一个体进行行为追踪和数据收集。随着技术的发展，基于大数据和开放数据共同构成的新数据环境已为新时代城市空间研究提供了有力支持<sup>[9]</sup> [如高德或百度等导航地图中的兴趣点数据 (POIs)、公交卡数据<sup>[10]</sup>、街景数据<sup>[11]</sup>等]，但个体数据的获取仍然存在困难。探索获取个体数据的有效方法将有助于弥补目前在研究个体行为与建成环境互动关系上的短板。

## 2 新设备发展

### 2.1 可穿戴设备

随着数字化和智能化的普及，新技术和新设备不断涌现。智能手环、智能手表等常见可穿戴设备已经可以通过人机交互记录佩戴者的身体状态和使用情况。目前应用于个体监测研究中的可穿戴设备大致分为两类：一种以状态监测为主，如阿米尔·穆阿雷米等<sup>[12]</sup>利用可穿戴胸带监测个体睡眠和心理压力情况，彼得·阿斯皮纳尔等<sup>[13]</sup>利用心电图传感器监测个体情绪变化；另一种以行为记录为主，如朴重勋等<sup>[14]</sup>利用计步器分析佩戴者的机体活动，乔治娜·布朗等<sup>[15]</sup>利用穿戴式相机 SenseCam 帮助健忘症患者记录日常活动。1945年，范内瓦·布什曾提

## 1 Background

Nowadays, with the refinement of user needs and spatial quality, more attentions are paid to improve user experience in urban design and renewal projects. Also, scholars have made their efforts in studying the relationship between individual behaviors and urban design. Since the 1980s, Yoshinobu Kuwahara<sup>[1]</sup>, Claire Cooper Marcus<sup>[2]</sup>, Jan Gehl<sup>[3]</sup>, and other pioneers have laid the foundation for the study on the relationship between human behaviors and space usage; Lawrence D. Frank et al.<sup>[4]</sup>, as well as Anne Vernez Moudon et al.<sup>[5]</sup>, conducted empirical research on the impacts of environmental factors within urban blocks on human behaviors; Chinese scholars including Xu Leiqing et al.<sup>[6]</sup>, Pan Haixiao et al.<sup>[7]</sup>, and Chen Yong et al.<sup>[8]</sup> have all focused on the changes of people's behavior within the environment by recording their activities in and interactions with the environment through observation, questionnaires, and interviews. Despite these achievements, few studies have focused on the behavioral characteristics of individuals in urban space. Limited by human labor and time cost, it has been difficult to objectively and continuously track and collect data of an objected individual in a long period of time. With the development of technology, the new data environment, formed by big data and open data, has provided a strong support for urban spatial research<sup>[9]</sup>, including Point of Interest (POIs) data, bus IC card data<sup>[10]</sup>, and streetscape data<sup>[11]</sup>. Yet, the acquisition of individual data is still difficult. Exploring effective methods to obtain individual data will help make up for shortcomings in the current study on the interactions between individual behavior and built environment.

## 2 New Device Development

### 2.1 Wearable Devices

With the dominance of digitization and intelligence, new technologies and new devices are emerging like mushrooms after rain. Common wearable devices such as smart bracelets and watches can record user's physical condition and activities via human-computer interactions. At present, in the research of individual monitoring, there are two types of wearable devices mostly used: one is used to monitor bio-signals. For example, Amir Muaremi et al.<sup>[12]</sup> used wearable chest belt to monitor individual's sleep quality and mental stress, and Peter Aspinall et al.<sup>[13]</sup> demonstrated how mobile electroencephalogram (EEG) can monitor individual's emotional changes. The other is used to record behaviors. For example, Park Jonghoon et al.<sup>[14]</sup> used uni- (LC) and tri-axial accelerometers (AM, ASP) to analyze

出“生命日志”的概念<sup>[16]</sup>，即使用智能设备全方位、全时段地记录个体生命特征，形成大量个体信息数据库，以数字化的形式记录个体自我活动，从而促进人们对人与环境互动关系的了解——这正是可穿戴设备的应用领域。

目前，可穿戴设备已经被应用在医疗健康、环境感知、数据分析等领域。在中国，尽管其发展还处于新兴阶段，但已被应用于多个学科的研究之中。例如范长军和高飞<sup>[17]</sup>从计算机科学的角度，尝试利用可穿戴传感器获取人体速度、生理信号等信息，并对深度神经网络识别人体活动的过程进行了讨论；冯雪和张丹<sup>[18]</sup>从社会心理学的角度提出利用移动传感技术采集心理和行为数据；虽然目前可穿戴设备在建成环境相关学科中的应用较少，但仍有学者在进行积极探索，如陈肇和刘颂<sup>[19]</sup>基于可穿戴传感器的情绪体验测量技术，采集人的生理信号，记录人在建成环境中的情绪变化；申悦和柴彦威<sup>[20]</sup>通过可穿戴GPS设备记录居民的移动轨迹，测度居民的空间活动范围。

## 2.2 穿戴式相机

20世纪70年代，史蒂夫·曼恩<sup>[21]</sup>基于人机交互概念研发出穿戴式相机。其后，随着微电子技术的发展，穿戴式相机也不断迭代更新，出现了SenseCam、GoPro、Narrative Clip等微型可携带相机，可提供记录个体活动的大量图片数据。

瓦伊娃·卡尼卡特等<sup>[22]</sup>发现由SenseCam相机拍摄的照片可有效增强个体对细节、情绪和偏好的记忆。姬玛·威尔逊等<sup>[23]</sup>邀请18名52~81岁的老人连续佩戴SenseCam相机一周，发现可穿戴设备比人们预想中更便于使用——使用者会日渐习惯佩戴，且几乎不会对其生活造成影响。亚伦·杜安等<sup>[24]</sup>利用视觉检测器来识别穿戴式相机获得的图片数据中的特征要素，如电脑、打印机、记事本等，从而对个体行为进行记录。诸如此类的研究已证实了穿戴式相机在记录个体活动与“生命日志”方面的优势。

另外也已有学者对穿戴式相机在建成环境中的应用展开了探索。例如，蒂莫西·钱伯斯等<sup>[25]</sup>邀请了168名11~13岁的新西兰儿童佩戴穿戴式相机，并辅以GPS设备记录他们的日常活动，收集其活动点分布及活动情况；安柏·L·皮尔逊等<sup>[26]</sup>利用穿戴式相机调查儿童日常亲水程度，通过分析每张图片中水体所占的像素比例和其他图片数据，识别出23种滨水活动并统计出佩戴者在滨水空间中停留的时间。尽管如此，利用穿戴式相机和图片分析来研究个体行为与城市空间之间的关系仍是一个新兴课题。

individuals' physical activities, and Georgina Brown et al.<sup>[15]</sup> used wearable SenseCam to help amnesiacs record daily activities. In 1945, Vannevar Bush proposed the concept of "lifelog,"<sup>[16]</sup> which means using intelligent devices to record individual life characteristics comprehensively and continuously, to form a large number of individual databases which record ones' activities in a digital way, in order to promote a better understanding of the interaction between humans and the environment. Nowadays, wearable devices have been applied to achieve this prospect.

Wearable devices have been used in fields such as medical health, environmental perception, and data analysis. Although it is still at the initial development stage in China, Chinese researchers have begun to more actively engage wearable devices in various disciplines. Fan Changjun and Gao Fei<sup>[17]</sup>, for example, discussed from the perspective of computer science about the process of applying wearable sensors to obtain individuals' movement information and physiological signals and identifying human activities by using the deep neural network; Feng Xue and Zhang Dan<sup>[18]</sup> employed mobile sensing technology to collect psychological and behavior data from the perspective of social psychology. Despite the applications in built environments are rare, scholars such as Chen Zheng and Liu Song<sup>[19]</sup> assessed real-time in-situ environmental affective experience by recording individuals' physiological signals obtained with wearable bio-sensors, and Shen Yue and Chai Yanwei<sup>[20]</sup> recorded the movement trajectory of community residents with wearable GPS devices to learn their daily reaching realms.

## 2.2 Wearable Cameras

In the 1970s, Steve Mann<sup>[21]</sup> developed a wearable camera based on human-computer interactions. Since then, with the development of microelectronics, wearable cameras have been continuously upgraded, bringing forth SenseCam, GoPro, Narrative Clip, etc. that have become common devices to record numerous image data of individual activities.

Vaiva Kalnikaitė et al.<sup>[22]</sup> found that photos taken by a SenseCam camera could effectively enhance an individual's memory of details, emotions, and preferences. Gemma Wilson et al.<sup>[23]</sup> invited 18 volunteers aged from 52 to 81 to wear SenseCam cameras for a week, and found that they gradually got used to wearing the cameras without inconvenience to their daily life, which revealed that wearable devices are more acceptable than expected. Aaron Duane et al.<sup>[24]</sup> recorded individuals' behavior by identifying the elements such as computers, printers, and notebooks from the images collected

### 3 实验设计

为了探索穿戴式相机在个体行为与建成环境关系研究中的应用,本研究试图利用穿戴式相机采集图片数据,并采用人工识别、调用计算机视觉分析应用程序编程接口(API)、利用Matlab进行色彩识别三种方式识别图片信息。随后,针对个体行为特征、时间分配、路径转移、场所事件等方面展开分析。具体研究框架如图1所示。

此次实验的预实验于2018年9月3日进行,正式实验时间为2018年10月8~14日(星期一至星期日),研究范围为测试者工作及生活的北京市海淀区清华园及周边地区。实验采用Narrative Clip二代穿戴式相机,每隔30秒拍摄一张照片,记录个体从清晨出门前至晚间到家后的所有经历(表1,2)。实验要求测试者将穿戴式相机佩戴在胸前,保证拍摄不受衣服、头发等物体遮挡,且镜头方向与个体前进方向一致(图2);另要求佩戴者每天卸下设备后及时导出照片并充电。实验结束后,测试者可删除涉及隐私的图片,随后由研究团队对剩余有效图片进行分析。由表2可知,在正常情况下,实验每日可获得1 200~1 500张图片,一周累计获得8 000~10 000张图片。

with visual concept detectors. All these research has evidenced the advantage of wearable cameras in recording individual activities and generating “lifelogs.”

Scholars have also explored the applications of wearable cameras in the built environment. For example, with the aid of GPS device, Timothy Chambers et al.<sup>[25]</sup> asked 168 children in New Zealand aged from 11 to 13 to carry wearable cameras to record their daily activity patterns. Amber L. Pearson et al.<sup>[26]</sup> used wearable cameras to investigate children’s daily access to water areas. By analyzing the image data such as the pixel ratio of water in the pictures, 23 types of waterfront activities and corresponding time spent were identified. Nevertheless, applying wearable cameras and the image analyses to study the relationship between individual behavior and urban space is still an emerging research interest.

### 3 Experiment Design

As an exploration that studies the relationship between individual behaviors and built environments with wearable cameras, this research attempted to capture image data and identify image information through three methods — manual image identification, image recognition with Computer Vision Application Programming Interface (API), and color calculation in Matlab. Researchers then analyzed the volunteer’s behavior, time use, movement path, and experiencing scenes. The research framework is shown in Figure 1.

A pre-experiment was carried out on September 3, 2018. The formal experiment was performed from October 8 to 14, 2018 (Monday to Sunday) in Tsinghua Campus and the surrounding areas in Haidian District, Beijing where the volunteer lives and works. The experiment used a Narrative Clip 2 wearable camera that takes a photo every 30 seconds, recording all kinds of the volunteer’s activities, from getting ready to work in the morning until arriving back home at night (Table 1, 2). The volunteer was asked to wear the camera in front of her chest and ensure that the shooting was not blocked by clothes or hair and that the camera faced the same direction as the individual moves towards (Fig. 2). The volunteer also needed to export the photos and charge the camera every day. Photos that involve privacy could be deleted by the volunteer before submitting the rest to the research team for analysis. Averagely, 1,200 to 1,500 images can be obtained per day, which makes a total of 8,000 to 10,000 images per week (Table 2).

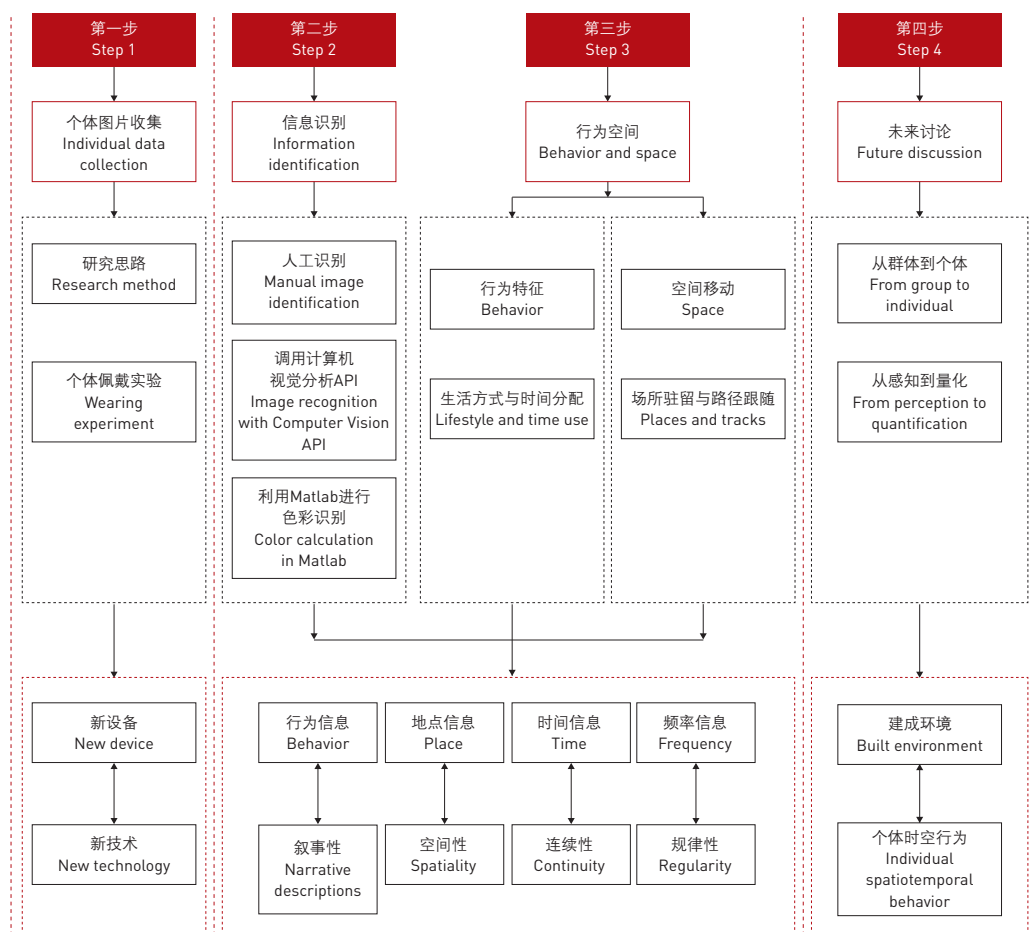


表1: 佩戴者个人信息  
Table 1: The volunteer's information

性别 Gender	年龄 Age	现居地 Location	职业 Occupation	身高 Height	体重 Weight	身体质量指数 Body Mass Index (BMI)	身体情况 Body condition	病史 Illness history
女 Female	26	中国北京 Beijing, China	科研工作者 Scientific researcher	158 cm	53 kg	22.4	健康 Healthy	无 N / A

表2: 图片记录情况  
Table 2: Collected data

	日期 Date	佩戴时间 Time period wearing the camera	照片总数 Total number of photos	有效照片数 Number of valid photos	天气 Weather
预实验 Pre-experiment	2018-09-03	9:30 - 22:30	1,455	1,446	晴 Sunny
正式实验 Formal-experiment	2018-10-08	8:00 - 22:30	1,283	1,272	多云 Cloudy
	2018-10-09	7:30 - 23:30	1,482	1,454	晴 Sunny
	2018-10-10	8:00 - 24:00	1,423	1,409	多云 Cloudy
	2018-10-11	7:30 - 21:30	1,306	1,287	晴 Sunny
	2018-10-12	7:30 - 21:30	1,274	1,254	多云 Cloudy
	2018-10-13	10:30 - 21:30	531 (设备电量不足) (Low battery)	531	晴 Sunny
	2018-10-14	10:00 - 24:00	1,260	1,253	多云 Cloudy

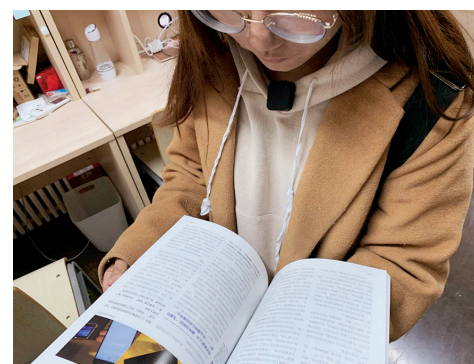
注:

1. 由于相机在没有任何指示灯提醒的情况下因电量不足而自动停止拍摄, 因此某些时段拍摄照片会相对较少。
2. 随着使用次数的增加, 设备的记录能力和续航能力均有所下降, 对实验结果造成了一定影响。

Notes:

1. Fewer photos were taken when the camera was in a low-battery and turned off automatically without indication.
2. The photography quality and battery life of the camera declined as the usage time increased, which somehow had an impact on the results.

2. 实验要求测试者将穿戴式相机佩戴在胸前。
2. The volunteer was required to wear the camera in front of the chest.



## 4 图片要素识别方法

### 4.1 人工识别

运用人工识别的方式识别图片信息主要是指通过对图片特征进行归纳和判断, 确定每张图片发生的地点、时间和事件。人工识别的优点在于对图片的解读更具体, 更能把握重点信息, 也能够对佩戴者行为进行常识性推测, 缺点是耗时较长。表3以2018年10月9日收集到的图片信息为例, 呈现了以人工识别方式对佩戴者全天行为的记录。但因佩戴设备电量不足, 因而未记录到其晚间通勤以及夜间活动的情况。全天共拍摄了1 482张照片, 其中有效图片1 454张。

## 4 Image Identification / Recognition Methods

### 4.1 Manual Image Identification

Manual image identification is to distinguish the location, time, and scene of each picture according to the image elements. It sees an advantage in accurately interpreting and grasping key image information to speculate the volunteer's behavior and experiencing scene. But it usually takes a very long time. Table 3 is a record of behavior obtained through manual image identification, taking the photos collected on October 9, 2018 as an example. Unfortunately, the volunteer's commuting and other activities at that night were not recorded because of the low battery. A total of 1,482 photos were taken, of which 1,454 were valid.

表3: 以人工识别方式记录的佩戴者全天行为  
Table 3: The volunteer's behaviors throughout the day identified by manual image identification

时间点 Time	事件 Scene	照片数 Number of photos	时长 (分钟) Duration (min)	时间点 Time	事件 Scene	照片数 Number of photos	时长 (分钟) Duration (min)	时间点 Time	事件 Scene	照片数 Number of photos	时长 (分钟) Duration (min)
8:30	出门前准备 Getting ready	20	10	约11:00 About 11:00	在工位上办公 Working in the office	68	34	约15:00 About 15:00	乘电梯上楼 Going upstairs by elevator	12	6
	步行下楼 Going downstairs	2	1	约11:30 About 11:30	步行下楼 Going downstairs	9	4.5		在工位上办公 Working in the office	200	100
	早间通勤 Commuting	39	19.5		前往食堂 Going to the dining hall	24	12	约17:00 About 17:00	走廊接水 Going to get drinking water in the corridor	7	3.5
约9:00 About 9:00	乘电梯上楼 Going upstairs by elevator	6	3		乘电梯上楼 Going upstairs by elevator	15	7.5		在工位上办公 Working in the office	87	43.5
	在工位上办公 Working in the office	104	52	约12:00 About 12:00	吃午饭 Having lunch	34	17		乘电梯下楼 Going downstairs by elevator	6	3
	交涉并盖章 Communicating and sealing the files	12	6		步行下楼 Going downstairs	10	5		前往食堂 Going to the dining hall	15	7.5
约10:00 About 10:00	前往科学研究院 Going to the research institute	11	5.5		返回办公室 Going back to the office	25	12.5		乘电梯上楼 Going upstairs by elevator	5	2.5
	步行上楼 Going upstairs	14	7	约12:30 About 12:30	乘电梯上楼 Going upstairs by elevator	12	6	约18:00 About 18:00	吃晚饭 Having dinner	29	14.5
	交涉并盖章 Dealing with administrative affairs	13	6.5		在工位上办公 Working in the office	184	92		步行下楼 Going downstairs	13	6.5
	步行下楼 Going downstairs	7	3.5	约14:00 About 14:00	乘电梯下楼 Going downstairs by elevator	7	3.5		返回办公室 Going back to the office	30	15
	前往财务处 Going to the finance office	20	10		打印文件 Printing documents	6	3	约18:30 About 18:30	乘电梯上楼 Going upstairs by elevator	10	5
	交涉并盖章 Dealing with administrative affairs	27	13.5		前往盖章处并盖章 Going to the administrative office and dealing with paper files	16	8		在工位上办公 Working in the office	298	149
	返回办公室 Going back to the office	10	5		走廊接水 Going to get drinking water in the corridor	6	3		电池电量不足, 未记录到更多结果。 No more information was collected because the battery had run out.		
	乘电梯上楼 Going upstairs by elevator	8	4		返回办公室 Going back to the office	33	16.5				

#### 4.2 调用计算机视觉分析API

利用Python语言调用计算机视觉分析API, 可以实现对图片中各类“标签”的识别, 并得到每张图片中的树木、车辆、水体、铺装、电脑、手机、笔、小孩、人群等元素。随后, 可以依据标签出现的连续性推导出个体行为及所在场所。这一自动化识别方式可以大幅提升效率, 但无法解读图片中的场所意义与行为特征。同时, 不分主次地识别图片要素会造成分析结果过于庞杂, 或识别出一些意义不明的标签(如“remote”“laying”“standing”“black”“white”等), 因此仍需人工识别进行核查(图3)。

#### 4.3 利用Matlab进行色彩识别

Matlab软件可识别图片中蓝色(天空)及绿色(植物)部分的比例(图4), 以判断图片是否拍摄于户外。虽然比较单张图片中蓝色或绿色的比例意义不大, 但可以有多张图片中蓝色或绿色比例持续较高的时间段进行标记, 再对比人工识别中对户外空间和绿色空间的识别情况, 验证Matlab的识别结果。举例而言, 若将蓝色视为天空且将蓝色比例较高(初步设定为60%及以上)的图片视为拍摄于户外, 那么如图5所示, 可以标记出可能处于户外的时间段(以橙色表示)。分析可

#### 4.2 Image Recognition with Computer Vision API

By using Python-based Computer Vision API, various labels could be recognized from the photos, such as “trees,” “cars,” “water,” “paving,” “computers,” “mobile phones,” “pens,” “children,” and “crowd.” An ongoing behavior or an invariant location can be derived from the repeatability of the labels. Although this automated identification leads to a great efficiency improvement, it helps little interpret the scenes or the volunteer’s behaviors. At the same time, the unfocused recognition of image elements often generates large-size analyses and blurred labels (such as “remote,” “laying,” “standing,” “black,” and “white”) that require an additional manual image identification to verify (Fig. 3).

#### 4.3 Color Calculation in Matlab

Matlab is primarily used to identify the ratio of the part in blue (sky) / green (greenery) of an image (Fig. 4) to distinguish whether the picture is taken indoors or outdoors. Comparing the ratio of blue or green in a single picture is of less meaning, while identifying the time periods in which the ratio of blue or green is relatively high may indicate that the volunteer was staying outdoors or accessing to greenery, which can be used as a cross-checking with the manual image identification result. In this experiment, the blue color represented the sky and a picture with a high blue ratio ( $\geq 60\%$ , preliminarily) was regarded as photographed outdoors, after

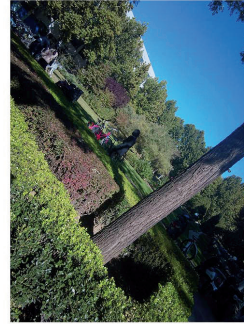
照片 Photos	计算机视觉分析API识别结果 Information identified by Computer Vision API	人工识别结果 Information obtained by manual image identification
	"outdoor" "man" "street" "riding" "bus" "car" "side" "road" "board" "red" "tree" "view" "city" "boy" "standing" "parked"	时间: 2018/10/09 12:10 地点: 校园道路 事件: 去吃饭 Time: 2018/10/09 12:10 Location: campus path Scene: going to the dining hall
	"indoor" "food" "table" "plate" "sitting" "desk" "holding" "black" "laptop" "people" "bowl" "woman" "man" "white"	时间: 2018/10/09 12:40 地点: 食堂 事件: 吃饭 Time: 2018/10/09 12:40 Location: dining hall Scene: having lunch
	"indoor" "person" "table" "sitting" "computer" "holding" "desk" "paper" "keyboard" "laptop" "man" "phone" "remote" "laying"	时间: 2018/10/09 15:40 地点: 办公室 事件: 工作 Time: 2018/10/09 15:40 Location: office Scene: working

3. 计算机视觉分析API和人工识别对同一组照片的识别结果

3. Comparison of the information acquisition by image recognition with Computer Vision API and manual image identification to the same photos

4. 利用Matlab识别出的蓝色及绿色比例
5. 人工识别和Matlab色彩识别的结果对比

4. The ratio of blue color and green color identified through the color calculation in Matlab
5. Comparison of the information acquisition by manual image identification and the color calculation in Matlab



绿色比例: 0.4828  
Green color ratio: 0.4828  
蓝色比例: 0.3152  
Blue color ratio: 0.3152



绿色比例: 0.1964  
Green color ratio: 0.1964  
蓝色比例: 0.2525  
Blue color ratio: 0.2525

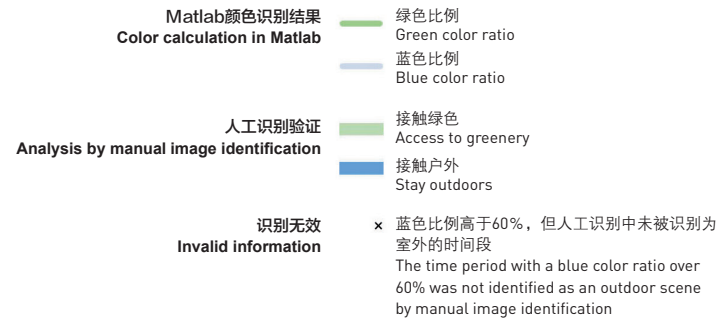
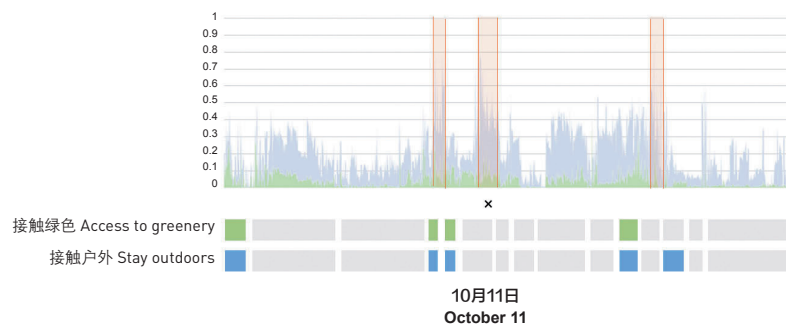
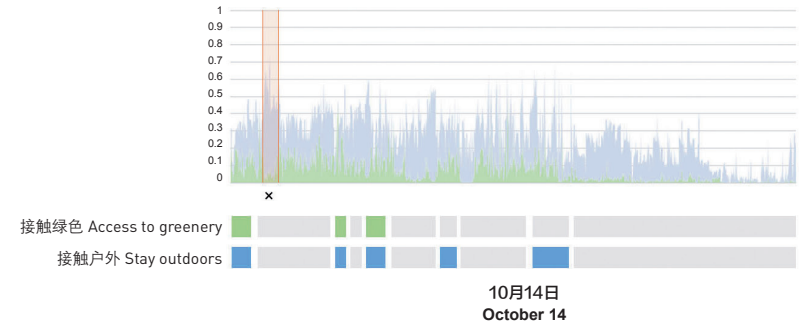
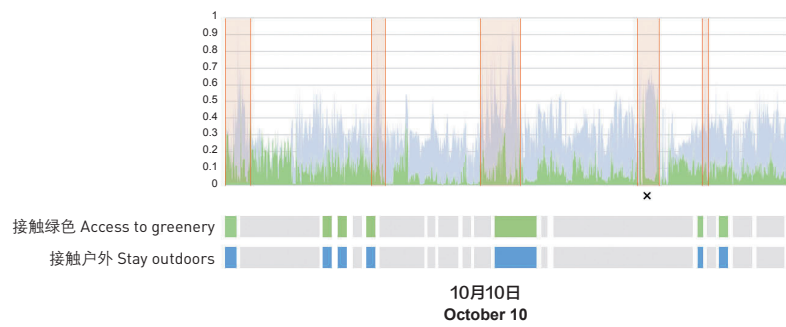
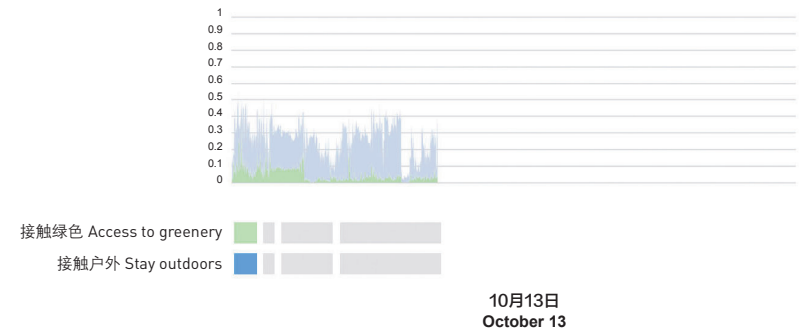
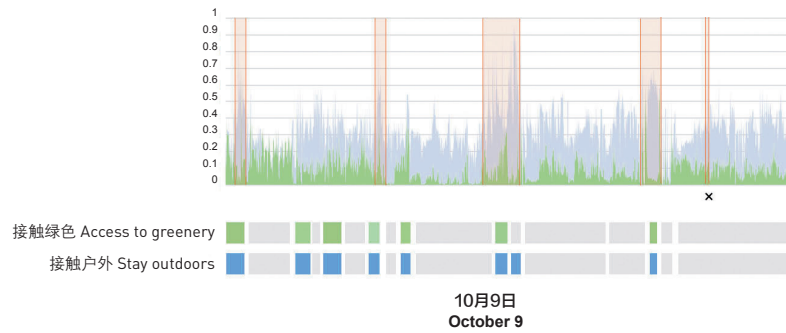
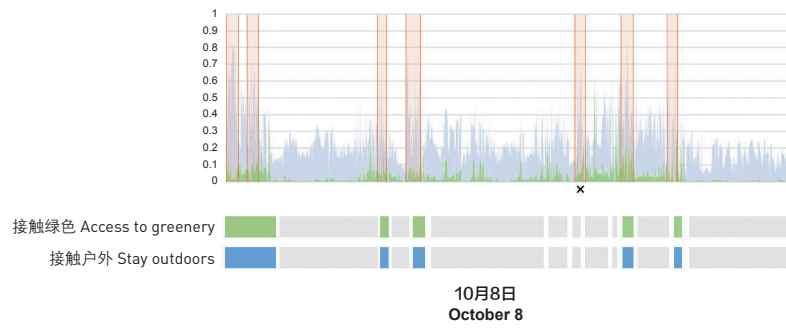


绿色比例: 0.0728  
Green color ratio: 0.0728  
蓝色比例: 0.6360  
Blue color ratio: 0.6360



绿色比例: 0.1740  
Green color ratio: 0.1740  
蓝色比例: 0.2524  
Blue color ratio: 0.2524

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得，Matlab识别出的29个户外时间段中有8段未包含在人工识别出的户外时间段之中，而人工识别出的37处户外场景中13处并没有呈现较高的蓝色比例特征。而出现偏差的主要原因在于：一方面，受相机位置和拍摄角度的影响，地面物体所占比例较大；另一方面，Matlab无法区分天空和其他蓝色物体，且在能见度较低或天色较暗的情况下，无法对天空进行识别。所以，此种方法更适合相机佩戴稳定、天色正常、无其他干扰的情况，且需要结合其他识别结果共同辨别。

#### 4.4 三种方法的对比与总结

在以上三种图片识别方式中，人工识别主要依靠佩戴者回忆及人工分析照片内容来读取图片中的时间、地点与事件信息，因而准确度较高，可以为后两种方法提供参考和验证，缺点是花费时间较长；调用计算机视觉分析API识别图片中的标签效率较高，具有一定的准确度，可以直接以数字化形式反映“是否在室外”“是否有人”等分析结果，适用于大规模的图片分析工作，但其可识别的标签有限，且较依赖技术支持；而利用Matlab进行色彩识别的局限性较大，一方面在于识别出的信息量较少，另一方面也较易受拍摄角度、天空能见度等外

which the time outdoors could be calculated (in orange in Fig. 5). Analyses showed that 8 of the 29 outdoor time periods identified by Matlab were denied with manual image identification; 13 of the 37 identified outdoor scenes did not see a high ratio of blue. The discrepancies might be caused by the following reasons: one is that, due to the position and shooting angle of the camera, not so much sky was photographed; the other is that Matlab cannot distinguish the sky from other blue objects, and more errors might appear when the visibility is low or the sky turned dark. Therefore, this method is more suitable for analyzing images shot in daytime and without interference. The recognition results need to be verified by other methods.

#### 4.4 Comparison of the Methods

Among the three methods outlined above, manual image identification relies highly on the volunteer's memory and manual identification on time, place, and scene. Its high credibility makes it often be used as a reference or verification for the other two automated methods. However, the process of manual image identification often costs a great amount of time. Image recognition with Computer Vision API sees efficiency and a certain degree of accuracy for specific label criteria, such as whether the photo is photographed outdoors or includes any person. It is applicable to large-scale analysis work, but an additional technical support is needed because of its limited recognition spectrum. Color calculation in Matlab also sees limitations in its recognition



6. 个体活动时间轴（2018年9月3日）
  7. 测试者的行为信息被概括为工作、通勤、就餐、社交和休闲5类。
6. The volunteer's timeline on September 3, 2018.
  7. The volunteer's behaviors included working, commuting, mealing, social activities, and relaxing.

部因素的影响。综上所述，后两种自动化识别技术的识别准确度仍有待进一步提升。

在本研究中，由于人工识别结果准确度更高，因此后续对于个体行为特征的分析是在人工识别结果的基础上展开的。

## 5 个体行为特征分析

### 5.1 时间分配与行为特征

穿戴式相机所建立的个体图片数据集蕴含着时间信息。由于照片间隔为30秒，因而可以根据图片出现的顺序和图片内容的重复性对佩戴者行为进行判读，并绘制出个体行为时间线。图6记录了预实验（2018年9月3日）一天的事件与时间信息，佩戴时间为9:30~22:30。通过计算图片数量，可以确定每种行为的起止时间和持续时间。

根据图片中各类要素出现的时间、频率及连续性对佩戴者行为模式进行量化统计，可将其行为信息概括为工作、通勤、就餐、社交和休闲5类（图7）；再依照这5类行为出现的时间和频率，对佩戴者一天

spectrum and susceptibility to external factors such as shooting angle and sky visibility. In summary, the latter two automated technologies need an improvement in recognition accuracy.

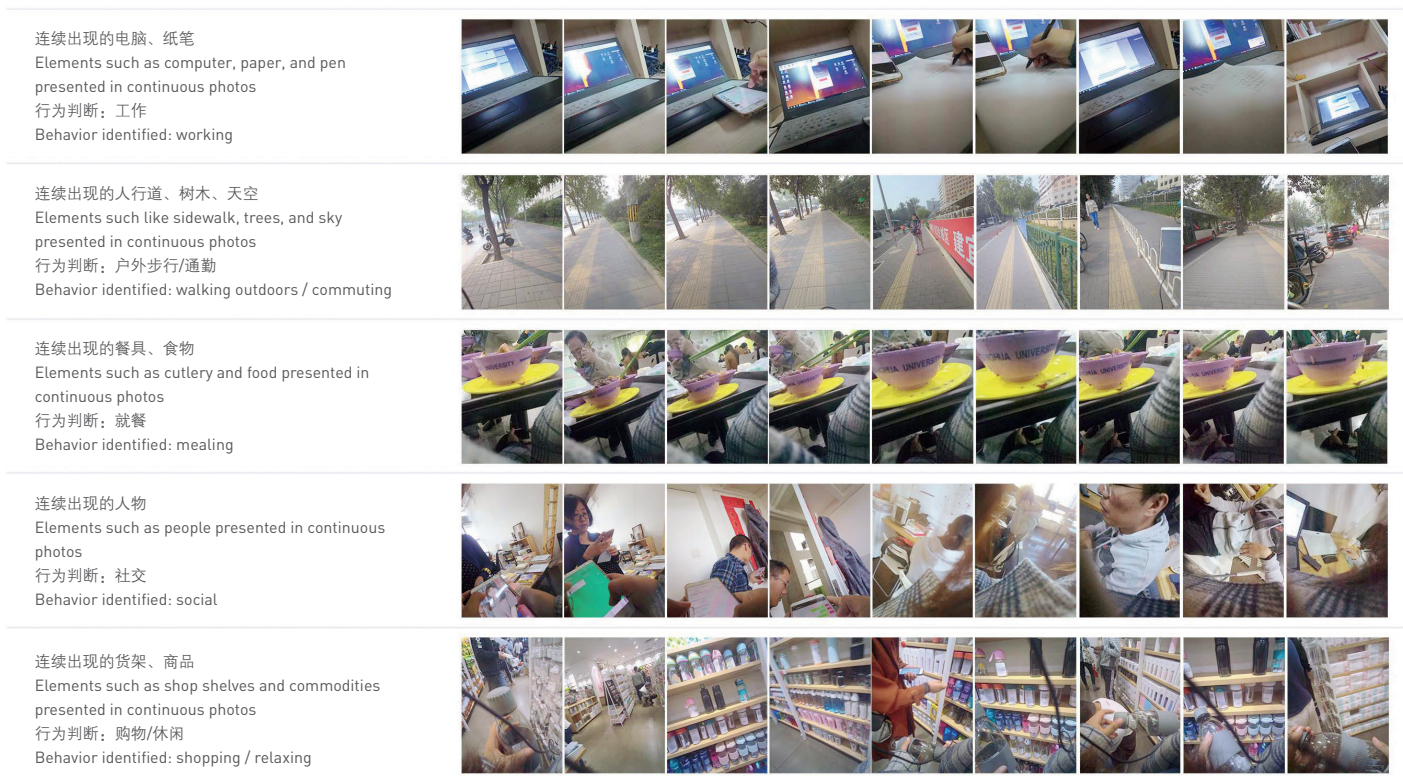
This study adopted the manual image identification method for the analyses of individual behavior characteristics due to the high accuracy of manual image identification results.

## 5 Individual Behavior Analysis

### 5.1 Time Use and Behavioral Characteristics

The image dataset of individual behavior recorded with the wearable camera is built upon time information. Since the photos were taken in every 30 seconds, the volunteer's behaviors can be interpreted according to the consequence of the pictures and the frequency of elements, profiling a timeline of the individual's behavior. The recorded data in pre-experiment (from 9:30 to 22:30 on September 3, 2018) is listed in Figure 6. The start and end time of each behavior and the duration of it were identified by counting the number of images reflecting a same behavior or a scene.

Depending on the duration, frequency, and continuity of various elements appeared in the pictures, the behavior information can be classified into five categories: working, commuting, mealing, social, and relaxing (Fig. 7). The volunteer's time use on each



的时间分配情况进行概括性表达（图8）。随后，通过对比每种行为在一周内的发生规律，可以在一定程度上了解个体行为特征（图9）。

## 5.2 空间转换与场所事件

首先，根据图片中的建筑以及道路信息可确定佩戴者的移动轨迹；其次，通过统计某段道路或某一地点的照片数量，可确定佩戴者通过或停留在某一场所的时间。图10呈现了佩戴者在2018年9月3日的空间转换及活动情况。通过识别图片中的位置信息并对佩戴者路径进行定位，可以绘制出空间转换地图与空间轴，以得到其行动路径与空间停留情况。

佩戴者一周内的活动范围与路径通过频率如图11所示（线条的粗细表示路径的重复次数）。一周中重复较多的路径为通勤路径，且每日通勤活动呈现出较强的一致性；就餐路径较为有规律，但仍有一定的选择性；休闲路径重复次数较少，规律性不强。其中，重复性和规律性较强的通勤路径、工作路径和就餐路径是个体生活的重要组成部分，体现出最短路径优先的倾向，而休闲路径是个体探索其周边环境的主观选择路径，体现出兴趣吸引的倾向，存在迂回和绕路现象，例如，个体会在周末选择途径商区较多的路径绕行回家。在该个体研究中，休闲路径体现出了个体在其周边社区环境中活动的最大范围。

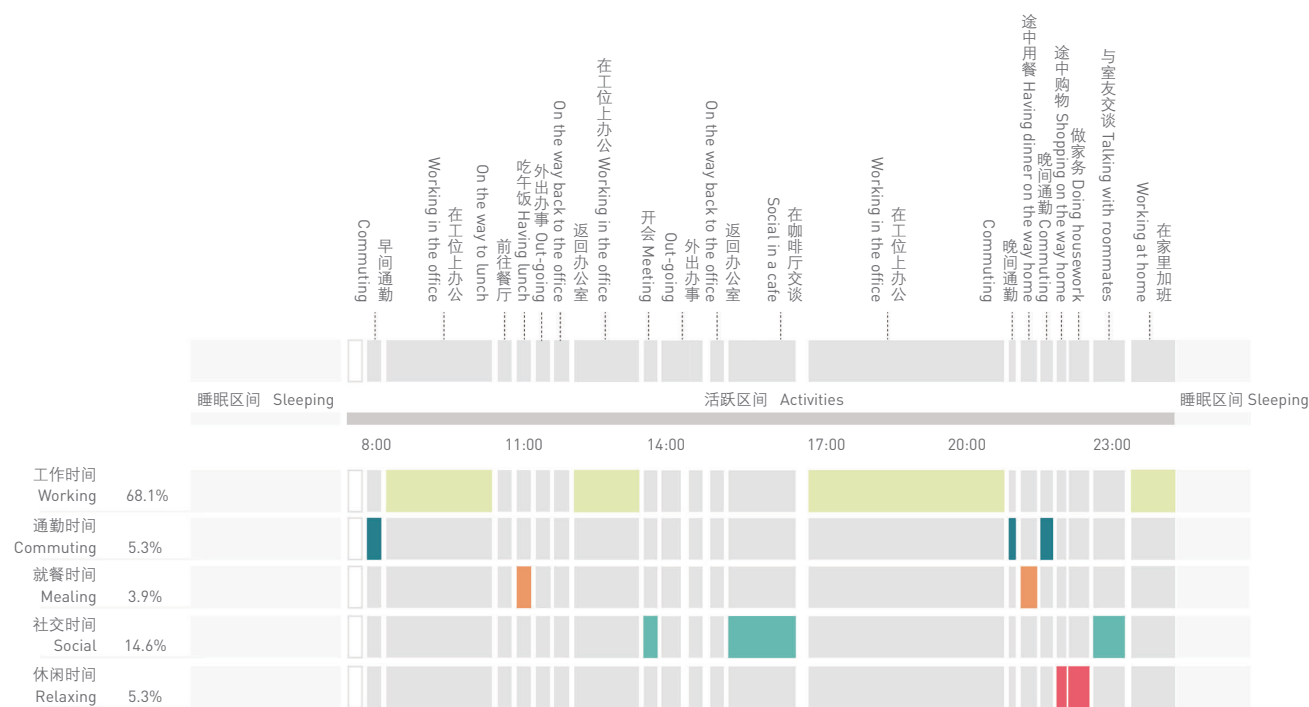
category can be described according to her behavior duration and frequency (Fig. 8), which provides a basis for studying her behavioral pattern over the week (Fig. 9).

## 5.2 Movement Path and Scenes

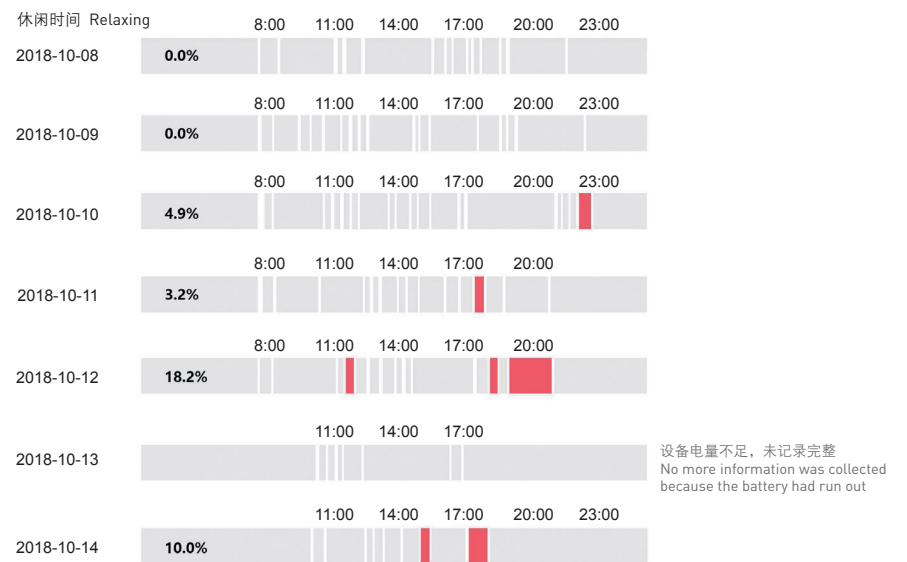
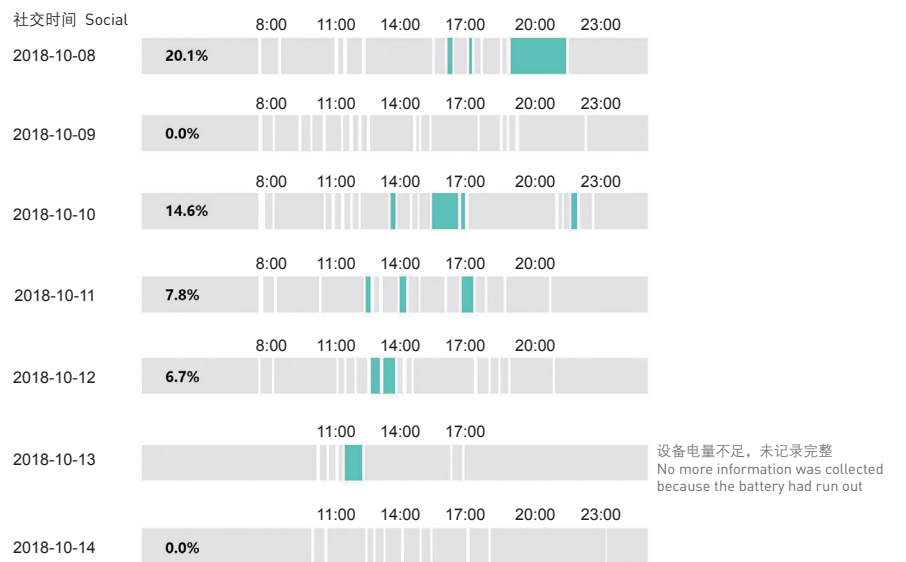
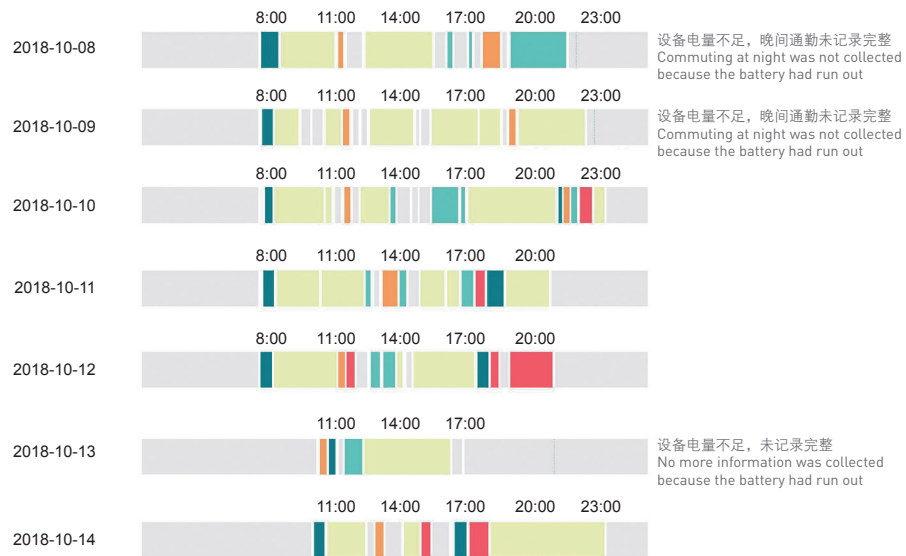
According to building and road information in the images, the volunteer's movement path can be identified, and by counting the number of images of a certain path or in a certain place, the duration in each place can be deduced. Figure 10 presents the volunteer's movement path and activities on September 3, 2018. A behavioral map and the spatial axis were formed to visualize the volunteer's movement and scenes.

The volunteer's daily reaching realm and movement lines are shown in Figure 11. The thickness of the line indicates the frequency of the routes — the thicker the line is, the higher frequency it is recorded. It can be concluded that the most repeated paths during the week were the commuting routes, which showed a strong regularity; the routes for lunch / dinner varied one or two times; the routes for relaxing saw a higher variety. The routes for commuting, working, and mealing, as daily necessities, showed a higher regularity because one is used to choose the shortest path. At the same time, one's route choice for relaxing is largely of impulsive uncertainty and personal preference, which often contains extra stops or detours. For example, on weekends, one often picks a way home with busy shops along, instead of the shortest path he / she commutes on

8. 个体行为的时间分配情况（2018年9月3日）
9. 个体行为的时间分配情况（2018年10月8-14日）
8. The volunteer's time use on September 3, 2018.
9. The volunteer's time use from October 8 to 14, 2018.



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同理，当个体活动范围扩大时，也可以描绘出个体在城市中活动的路径，但城市范围中的路径研究需要考虑到不同交通方式的转变，在此不做赘述。

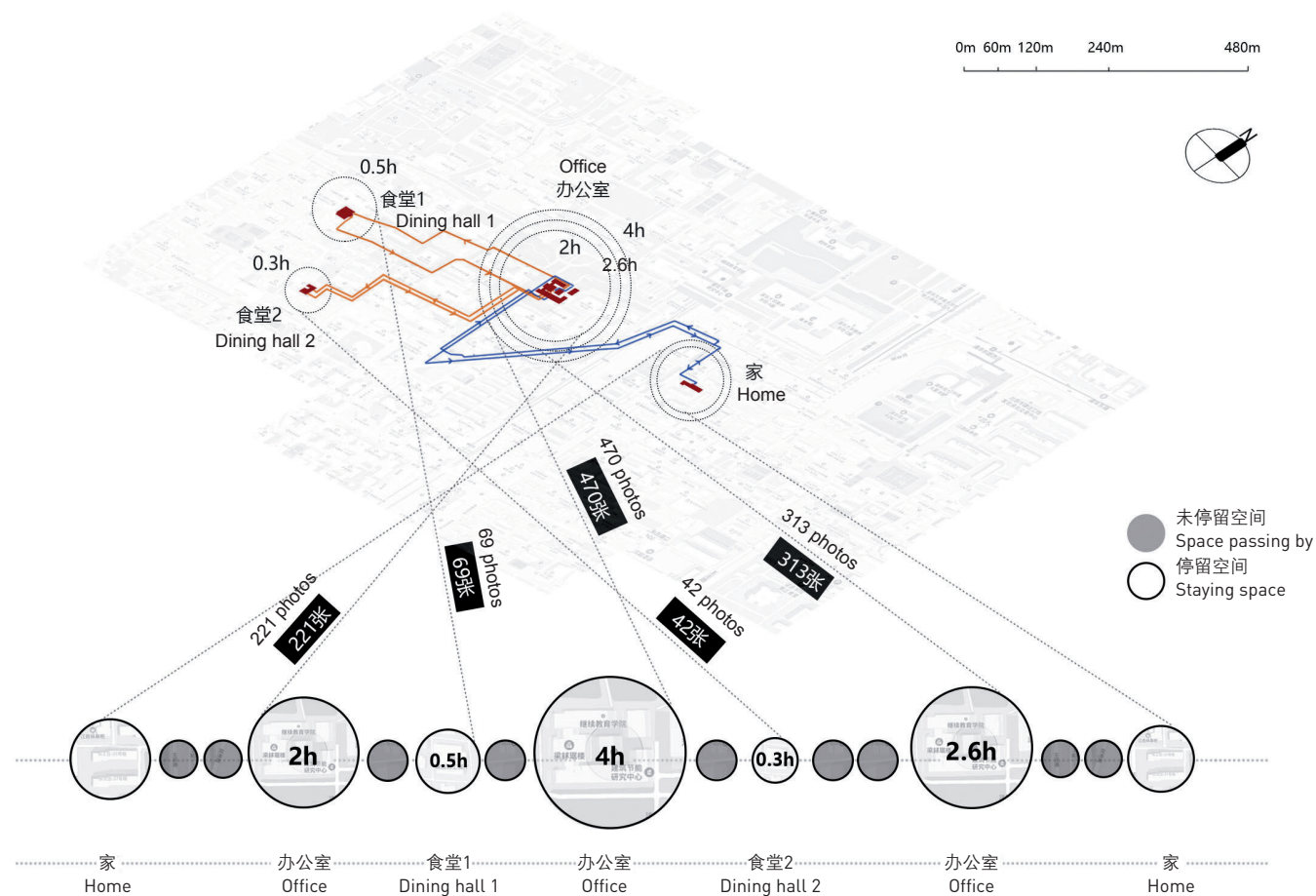
## 6 总结与反思

穿戴式相机提供的大量个体行为图片数据库记录着丰富的时空信息，这一数字化的自我行为记录为研究个体“生命日志”提供了硬件支持。通过人工识别、调用计算机视觉分析API和利用Matlab进行色彩识别等方式，对图片中的时间、地点、事件等要素进行识别，能够进

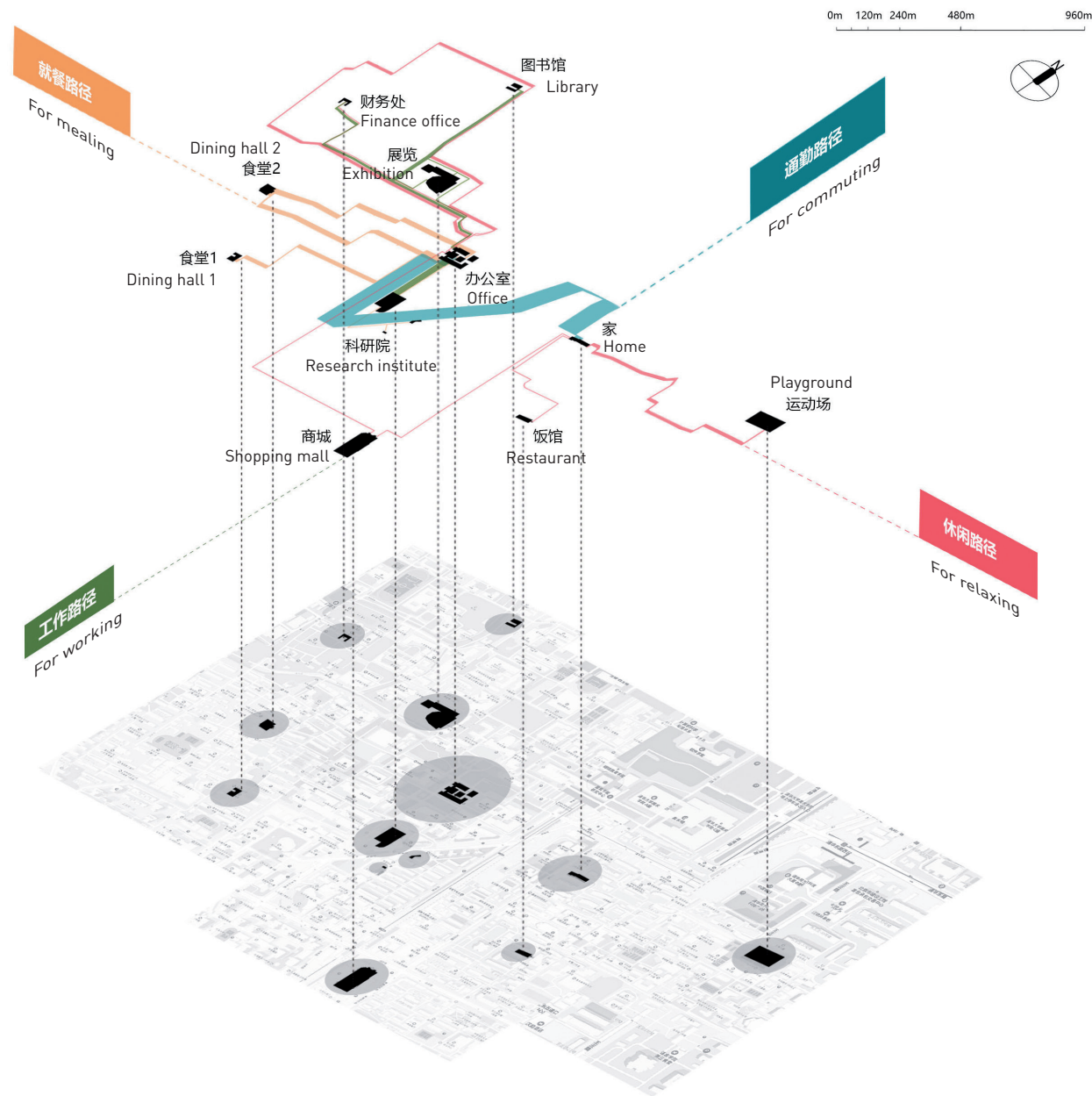
working days. In this study, the movement paths in the volunteer's relaxing activities defined her reaching realm in the experiment site. Similarly, as the realm expands, an individual's movement path can be depicted at a city scale; however, a city-scale research often has to consider the impact of different transportation modes on individual's behaviors, which is not expanded in this research.

## 6 Summary and Review

The large-sized image database of individual behavior recorded with wearable cameras is built upon rich digitalized spatiotemporal information. It works as a basis for studying individual activities in a form of "lifelog." Through methods including manual image identification, image recognition with Computer Visual API, and color calculation in Matlab, specific time, locations, and scenes can be identified to form and visualize the volunteer's behavioral timeline, time use, and movement path. It profiles an overall behavioral pattern that not only demonstrates the effectiveness of



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10. 个体活动地点轴 (2018年9月3日)
11. 个体行为的空间转换情况 (2018年10月8-14日)
10. The volunteer's movement timeline on September 3, 2018.
11. The volunteer's movement in daily scenes from October 8 to 14, 2018.

一步得到个体行为的时间轴、时间分配图、空间轴和路径图等, 可对个体行为进行较为全面的描述, 从而印证了个体大规模图片数据库在分析个体与城市空间互动关系方面的有效性, 也是将穿戴式相机应用于建成环境领域研究的一次全新尝试。

受实验成本限制, 本文以单一个体参与者为研究对象, 具有一定的局限性, 未能通过对比实验进行相互验证。但通过对个体佩戴经历的记录和对图片分析技术手段的研究, 本实验亦积累了一定经验: 如

image database in analyzing interactions between individuals and urban space, but also illustrates a new application of wearable cameras in built environment studies.

Limited by the fundings, this experiment only invited one volunteer, lacking a check experiment. However, several conclusions and lessons can be drawn from the volunteer's wearing experience and the exploration in image analysis. Firstly, the shortages of the Narrative Clip 2 wearable camera include short battery life, occasional equipment failure, poor photography quality in dark conditions, unstable shooting along moving, and file missing. In future experiments, the use of wearable cameras

发现Narrative Clip二代穿戴式相机存在电池续航能力不足（且会随着使用次数的增加而持续下降）、偶发设备故障、夜间拍照质量较低、运动时镜头不稳定、图片储存丢失等情况。在日后更多的实验中应尽量规范佩戴者的使用方法，维护设备正常运行（或尝试使用其他设备甚至是定制穿戴式相机）并保证图片质量。此外，由于实验采用的穿戴式相机本身不具备记录坐标的功能，因此需要人工读取图片中的地理位置，若能配合使用穿戴式GPS设备，则可以获得更加准确的地理位置信息。

## 7 穿戴式相机的未来应用

随着大数据的出现，基于建成环境层面的形态要素数据和多种互联网数据开展的针对大规模群体的研究，为利用大数据解释城市问题提供了大量案例参考，并逐步建立了理论基础。然而，这样的大数据仍较难被应用于对个体进行深层次解读。穿戴式相机为大规模采集个体数据提供了可能，通过将个人活动信息数字化，形成“数字自我”的电子化记录，弥补了现有研究中对个体行为数据采集不够连续、维度不够丰富的问题，这也是从城市环境数据化向个体行为信息化的转变之一（图12，13）。同时，个体行为信息化也将推动研究方法的革新和新技术的介入，从主观的“个体感知”转向客观的“量化研究”。

本研究通过对具体技术路线进行讨论，证实了穿戴式相机在研究个体行为与建成环境互动关系上的可能性与有效性。一方面，穿戴式相机以及其记录下的大量个体图片信息为未来研究场地与个体行为提供了技术支持；另一方面，穿戴式相机也可以应用在城市空间调研和空间评估实践中，包括使用者行为调研、场地使用状况追踪、城市设计品质与活力评估等方面。其未来在研究个体与城市空间互动关系方面的潜力非常值得期待。LAF

should be standardized to ensure the device working and the photography quality. Secondly, given that the wearable camera does not record coordinates, location data needs to be read manually. A combination with wearable GPS recording can efficiently facilitate the acquisition of geographical information.

## 7 Prospects of Wearable Cameras

With the advent of big data, large-group studies on built environments with supports from formal element data of the built environment and Internet data have provided a reference for interpreting urban problems through the lens of big data and laid a theoretical foundation. However, it is still difficult to apply big data at an individual level. Wearable cameras provide a possibility to collect massive individual data and to digitize the individual behaviors in an electronic form of “quantified self,” promoting the continuous and multidimensional collection of individual behavior data. It also echoes the shift from the digitalization of urban environmental data towards the digitalization of individual behavioral data (Fig. 12, 13). At the same time, the information level of individual behavior will also promote innovation in research methods and technologies. With this drift, research based on individual perception will turn into quantitative studies.

This study proves the possibility and effectiveness of using wearable cameras for studying the interactions between individual behavior and the built environment through an exploration on the technical roadmap. Wearable cameras and the collected images provide technical support to future research on space and individual behaviors. Moreover, they can be applied to urban spatial investigation and assessment for further research on user behavior, site usage tracking, and the evaluation of urban design projects. It is particularly promising to apply wearable cameras into the studies on the interaction between individuals and urban space. LAF

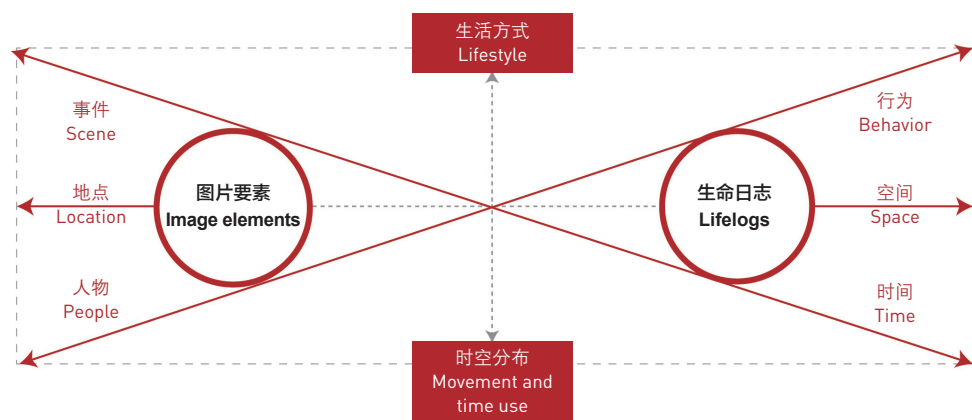
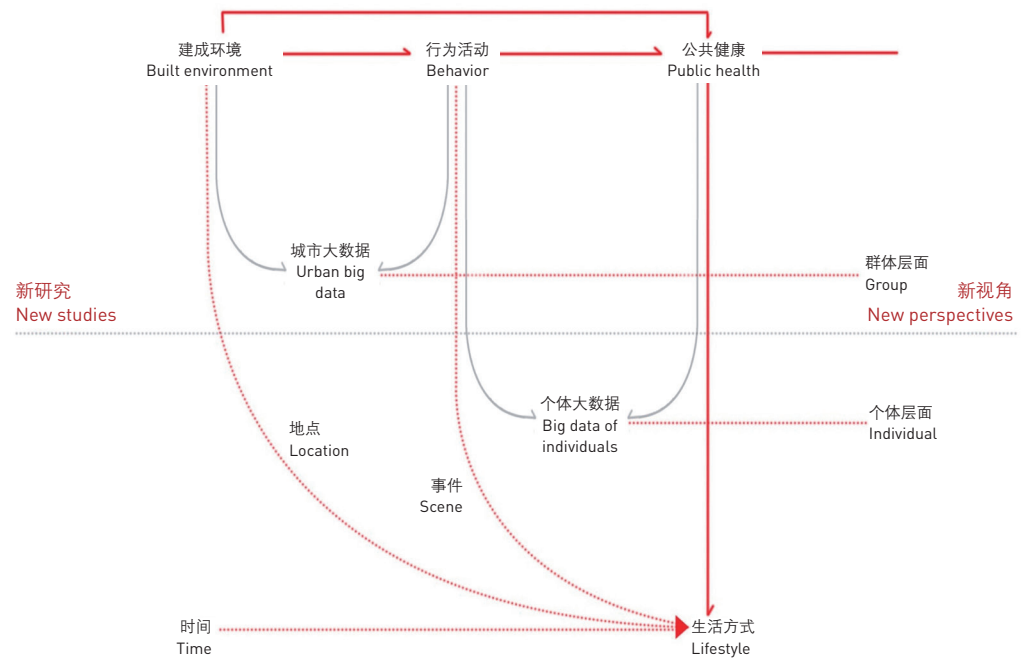


图12  
12

12. 利用图片研究个体空间行为
12. Studying individual's behavior based on image identification / recognition.

13. 未来研究将从关注群体层面转为更加关注个体层面。

13. Researchers in the future are expected to pay more attention from group study to individual study.



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