Zhan, X, Guo, FB and Roberts, E

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Tourism Recreation Research

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rtrr20

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To cite this article: Xiaochun Zhan, Fang bin Guo & Emma Roberts (2023): Image-based research methods for mapping tourist behaviour: smart photos, Tourism Recreation Research, DOI: 10.1080/02508281.2023.2196487

To link to this article: https://doi.org/10.1080/02508281.2023.2196487

Published online: 21 Apr 2023.

TOURISM RECREATION RESEARCH
https://doi.org/10.1080/02508281.2023.2196487

Routledge
Taylor & Francis Group

Research Note

Image-based research methods for mapping tourist behaviour: smart photos

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ABSTRACT
Conventional research methods for understanding tourists' behaviours need to be more practical and accurate when tracking tourists' movements within a destination. In recent years, technological development has offered advanced technical approaches for data collection and analysis. Taking account of the tourist experience in post-industrial landscapes, this study introduces an image-based methodology to explore tourists' movements at industrial heritage sites. Preliminary results are presented, using Liverpool's Royal Albert Dock as an example of detecting tourists' movement through use of a drone. The findings demonstrate that the selected method – Smart Photo – effectively maps tourists' behaviour and movements, and that this provides researchers with a simple, fast, and accurate data collection and analysis tool.

ARTICLE HISTORY
Received 22 November 2022
Accepted 15 March 2023

KEYWORDS
Post-industrial sites; Albert Dock; tourist movement; drone; background subtraction; research methods

Introduction

Post-industrial sites offer cultural heritage attractions which exhibit diverse architectural periods and styles, a sense of place, and a pedestrian scale, to provide distinctive tourist experiences (Toha & Ismail, 2015). Understanding tourists' movement patterns in such sites is an essential indicator and predictor of future tourist behaviour for all tourism stakeholders (Pearce, 2005). It is also a measurement of assessing designers' work and the drivers for their future design. The measurements will inform project investors and designers in planning tourist flows to avoid overcrowding, to minimise adverse impacts on a sensitive destination, to identify potential places for leisure activities, to advise on transport policies, and more broadly to distribute expected benefits.

Tourists' movement patterns can be divided into inter-destination and intra-destination (Raun et al., 2016). Inter-destination movements refers to tourists moving from their origin to one or more destinations, while intra-destination movements refers to tourists transferring among attractions within a city or moving around within an attraction (Raun et al., 2016). Clarifying intra-destination movements will optimise the initial planning of a project to enhance the tourist experience. Substantial efforts have been made to map the inter-destination movements; however, researching intra-destination movements has been inhibited by several practical methodological challenges (Toha & Ismail, 2015). Traditional methods of investigating intra-destination movements have been critiqued for their accuracy (Shoval & McKercher, 2017; Hardy et al., 2022). This study proposes an image-based methodology for the purpose of detecting tourists' movements, with the objective of offering a practical, efficient, and reliable method for data collection and analysis. The efficacy of the proposed method is demonstrated through its application to Liverpool Royal Albert Dock as a case study.

Review of current methods

Observation was used to record tourists' itineraries (Donaire & Galí, 2008), whereby the researcher follows the tourists from a distance to record their activities and routes (Hartmann, 1988). This method allows researchers to observe all activities undertaken by the respondents and to track the tourists. However, it requires intensive time consumption to follow a large number of tourists.

Qualitative Interviewing is a method which explores tourists' intended activities in order to detect tourists' travel itineraries (Oppermann, 1995). This method is flexible in collecting in-depth tourism information and possesses the advantages of being low-cost and enabling relatively large sample sizes. However, the method relies

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on the respondents' statements and is subject to the general imprecision of the frequency, sequencing, and duration of activities; therefore, detecting information is problematic (Pettersson & Zillinger, 2011).

Sketching trips on a map is a stochastic method that requires tourists to draw their route on a map, indicating their movement patterns (Mckercher & Lau, 2008). This method visualises a tourist's route directly to help the researcher extract information quickly. However, it requires additional details to be collected from activities and is limited by tourists' capacity for recall and memory accuracy, resulting in the production of problematic data. In addition, it is complex and challenging for researchers to document and understand hundreds or thousands of individual routes.

Trip diaries are a commonly used method for detecting itineraries of tourists. Tourists are usually required to complete their travel diaries during their visit to a destination, to record their activities and locations in each period (Prelipcean et al., 2018). Trip diaries provide a more comprehensive picture of tourist activities and offer detailed information on spatial and temporal activity patterns. While several automated and semi-automated travel diary methods are currently being developed (Hesjevoll et al., 2021), in many cases, the primary measure of travel behaviour remains a self-reported activity due to cost and feasibility (Kang et al., 2018; Vardhan et al., 2022). Unfortunately, self-reported travel surveys rely heavily on the respondent's ability and willingness to provide correct and precise information; the resultant data is susceptible to human error, such as recall or social desirability bias (Ellis et al., 2014).

Modern technology, such as the Global Positioning System (GPS), allows researchers to collect data efficiently by asking participants who are wearing a GPS device to track their location during a visit (De Cantis et al., 2016). The method benefits from accurate data, easy analysis, and low time consumption (Vardhan et al., 2022). In many cases, however, there may be cost limitations. Likewise, Digital Footprint tracks and analyses tourists' activity/behaviour through the trail of data they left on the internet (Girardin et al., 2008). It is a cheap and fast approach that can collect large amounts of data. Unfortunately, the method is more applicable to macro-tourism scenarios than micro-tourism due to its lack of identifying detailed tourists' movements within a destination.

As this study emphasises mapping tourists' behaviour and movement within destinations, high accuracy, availability, appropriate technique, efficient time frame, the privacy of travelling and affordable price are the main criteria for selecting the method. However, the research methods described above cannot fully satisfy the requirements, as a tabular comparison between them demonstrates (Table 1).

Methodology development

A Smart Photo technique was developed to map tourists' movements using two major phases, which were video recording and people detecting, and movement mapping.

Video recording and people detecting

During the first phase, a drone carried a video camera to record 20 min of video with set of Full HD resolution of 1920×1080 pixels and a frame rate of 60fps. The shooting angle could be adjusted to capture images with a flexible perspective. The method requires automatic recognition of moving targets from the video. While there are existing applications for detecting people in video, they usually rely on Face Recognition Technique, which is ineffective in this case as the videos do not contain human faces. In addition, these applications suffer from the inadequate ability to reduce environmental distractions, such as water reflections and birds. Considering this problem, an application has been developed by researchers to detect people in videos: Smart Photo.

Currently, there are three major techniques, Optical Flow (OF), Interframe Difference (ID), and Background Subtraction (BS), which are widely used in current moving target detection (Rymel et al., 2004). OF is the motion of the instantaneous movement of space velocity on the viewing plane to detect the moving objective (Shafie et al., 2009), while ID works by detecting the moving targets by comparing two or three continuous images (Cheng & Wang, 2014). Similar to the ID, the BS subtracts current frame images from a continuously

Table 1. Characteristics of different methods.

Method characteristics	Observation	Interview	Sketching trip on the map	Trip diary	GPS	Digital Footprint
High accuracy					✓	✓
Time-efficient					✓	✓
Cost-efficient	✓	✓	✓	✓		✓
Large sample size					✓	✓
No active visitor participation required						✓
Real-time					✓	✓
Easy to analyse data					✓	✓
Flexible in location	✓	✓	✓	✓	✓	

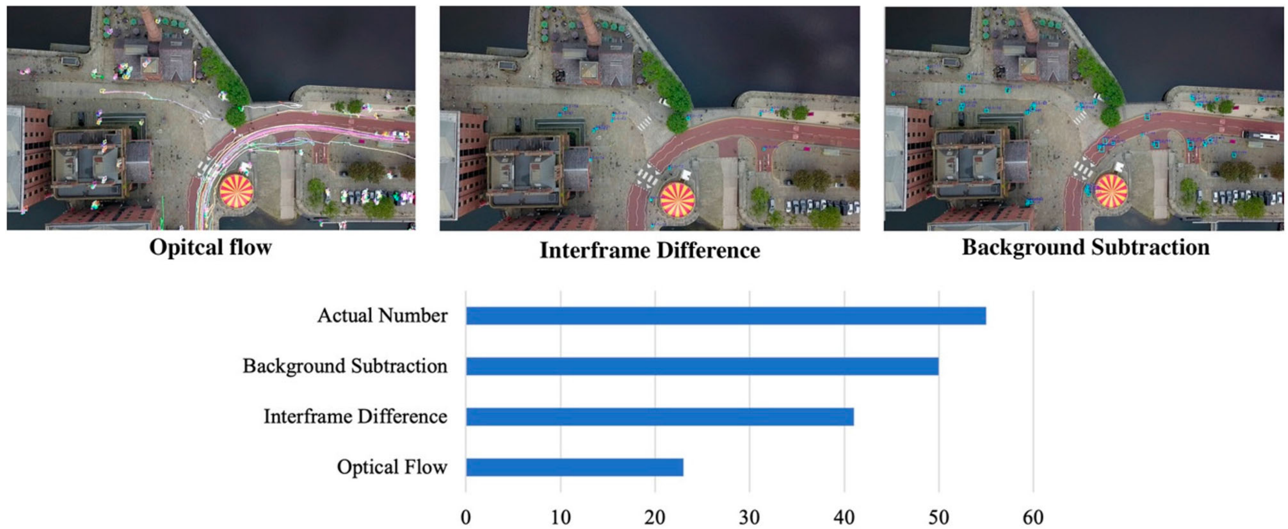

Figure 1. Comparison of three approaches.

updated background instead of subtracting from the adjacent frame image to extract moving objects in different images (Garcia-Garcia et al., 2020). After a comparative test of these three techniques, BS appears to be the best option in terms of accuracy that satisfies the project requirements. The OF image demonstrates that each optical flow represents a detected tourist, and the blue boxes in the ID and BS images represent detected tourists, so apparently, the BS count result is closer to the actual number (Figure 1). Therefore, the application in this study is based on BS technology, developed by python language and OpenCV library to detect people in aerial view videos.

Figure 2 illustrates the workflow of People Detecting. Firstly, a detection area is selected to minimise distractions from the surrounding environment. The next step is to acquire the background image, which is obtained by converting all image frames from RGB format to greyscale and averaging the corresponding greyscale values of all frame images. This process effectively eliminates the presence of people in the background image. To detect people, the image-frames with people are subtracted from the background image which enables the detection of people by the Gaussian Mixing Model (GMM) approach. Finally, from this process, people are marked automatically in the image.

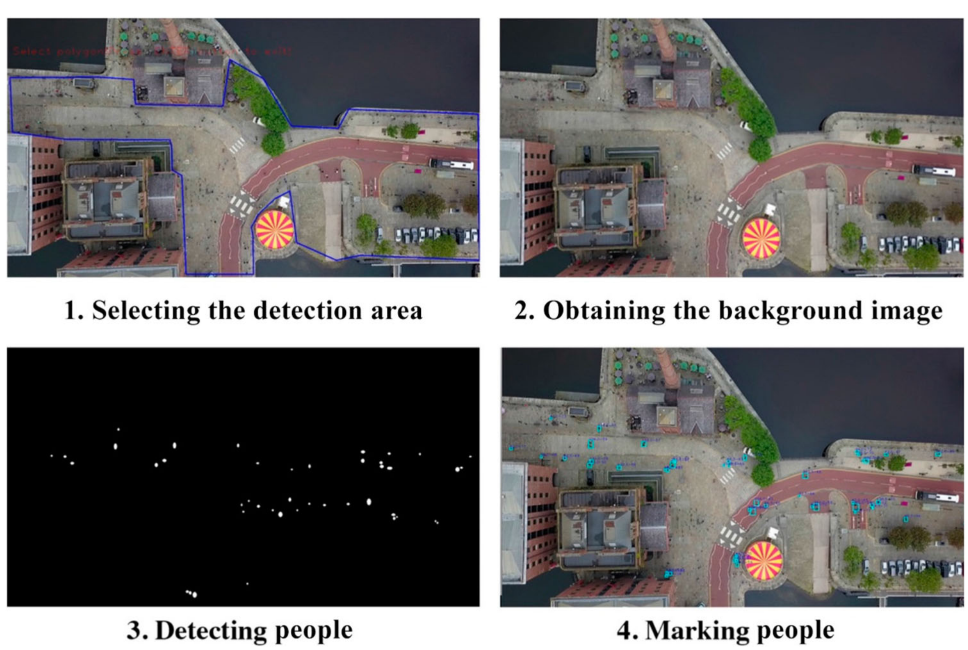

Figure 2. The workflow for the detection of people.

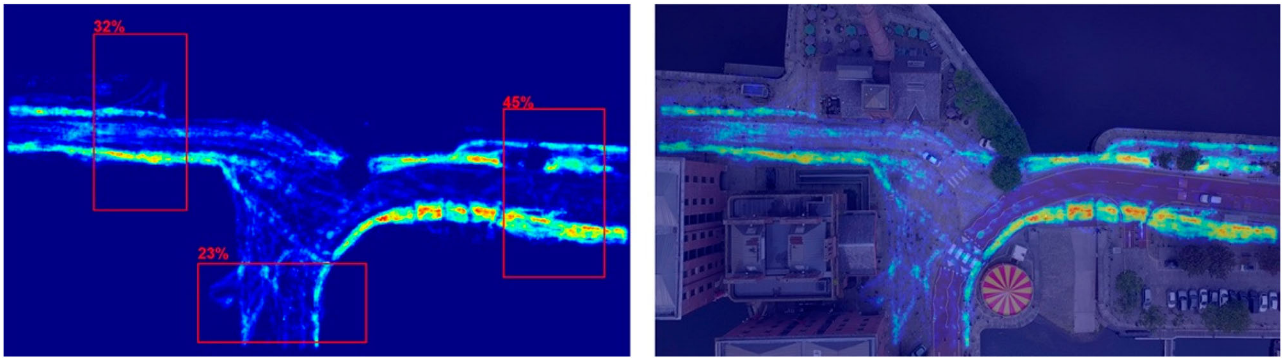

Figure 3. Heat map of the Royal Albert Dock.

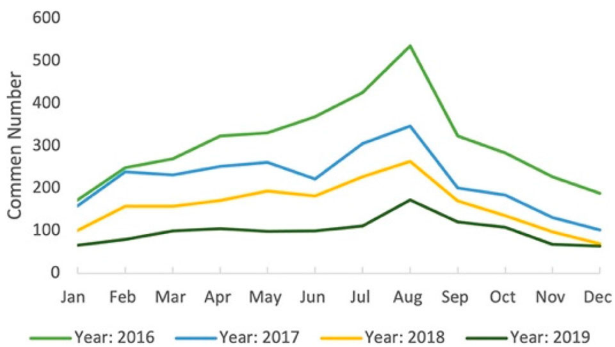

Figure 4. The data from TripAdvisor

Figure 5. Six locations are recorded in the Royal Albert Dock.

GMM is the most effective technique for modelling the background and foreground state of pixels (Bouwmans & El Baf, 2010) and has the ability of universal approximation as they can fit any density function if they contain enough mixture (McLachlan & Basford, 1988). Thus, GMM was selected to initialise the background in this study. The expression of background is as follows:

$$B(x, y) = GMMf_k(x, y)\ k = 1, 2 \ldots n \qquad (1)$$

where B is the background, n is the total number of frames selected.

After obtaining the background image frame B, the differential image $D_n(x, y)$ is expressed as:

$$D_n(x, y) = |f_n(x, y) - B(x, y)| \qquad (2)$$

where $f_n(x, y)$ is recorded the current video image frame.

The people can be detected by:

$$R_n(x, y) = \begin{cases} 1\ D_n(x, y) > T\ \textit{Detected people} \\ 0\ D_n(x, y) \leq T\ \textit{empty road} \end{cases} \qquad (3)$$

where T is the greyscale threshold.

Movement mapping

In response to study requirements, the application also includes a movement mapping function that automatically generates a heat map with tourist distribution data (Figure 3). The heat map consists of the thermal values of each frame image. The thermal value $H_n(x, y)$ for the nth frame of a pixel can be expressed as:

$$H_n(x, y) = \sum_{0}^{n} R_n(x, y)/n \qquad (4)$$

where n is the number of a recorded video frame; $R_n(x, y)$ is the nth frame of the tourist at *(x, y).*

Furthermore, the usage rate of each route O_r can be calculated. The formula is:

$$O_r = \sum_{0}^{n} H_n(mean)/n \qquad (5)$$

where $H_n(mean)$ is the average heat value in the detection area at n frame.

Case study and data

To demonstrate how the proposed methodology maps tourist behaviour, Liverpool's Royal Albert Dock is

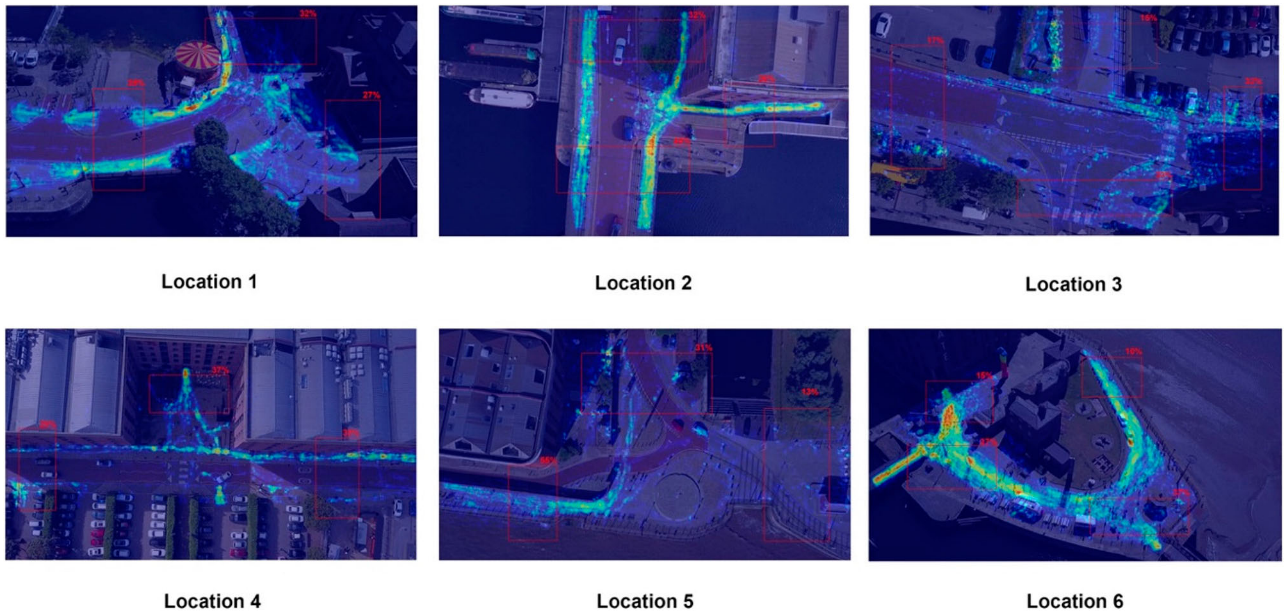

Figure 6. The heat maps at junctions.

chosen as a case study. Famous for its unique architecture, home to The Beatles Story, the Tate Liverpool and the Merseyside Maritime Museum, the Royal Albert Dock has long been a Liverpool landmark, in addition to being the most visited industrial heritage attraction in the UK outside of London, with over four million visitors each year (Spirou, 2010). The timing and location of data collection are crucial factors, and the researchers expected visitor data to be available at peak times to inform the results in this study. Hence, the data was collected in August based on information from the online travel advice site, TripAdvisor (Figure 4). Six key junctions were selected that encompass all paths throughout the dock, providing a clear view of the tourists' movement (Figure 5). Multiple data collections and experiments were conducted and were averaged to ensure their reliability.

The findings provide heat maps of each location. The redder the colour, the higher the density of tourists (Figure 6). It is evident that there are more tourist clusters at locations 1, 2, and 6. Further calculations of usage rates can be derived (Figure 7). The external routes at Albert Dock are more heavily utilised than the internal paths. These passageways were colour-coded by the researchers to illuminate their usage. Specifically, the red line paths have the highest usage rate at 27.79%, while the orange and yellow line account for 22.07% and 21.8%, respectively, followed by the blue line at 16.51% and the green line at the least at 11.83%.

Preliminary results reveal two potential problems at the Royal Albert Dock. Firstly, Location 6 is overcrowded at peak times, and the red line is significantly more heavily used than elsewhere. Secondly, the lower usage of the internal (the green line) route means that few tourists enter the historic building to visit or consume, instead preferring to walk along the riverside. It is worth noting that most businesses of the Royal Albert Dock have their 'frontage' on the 'green line', even though the data indicates that this area has the lowest proportion of footfall, with 88% of movement occurring around the exterior. This finding demonstrates that while the Royal Albert Dock is a popular post-industrial attraction, there is potential for improvement in spatial planning, a topic that warrants further contemplation by planners and designers.

Overall, the Smart Photo method has been proven to be the most effective and has demonstrated several advantages over conventional approaches in terms of its accuracy, high data volume, and time-savings. Moreover, compared to other techniques, this method also costs less and protects privacy in travel, as researchers do not require intervention in the tourist's movement, which assures the objectivity and validity of data collection (Table 2).

Conclusion and future research

An image-based method – Smart Photo – was introduced to map tourist behaviour in post-industrial sites, which acquired video data via drones and used the BS technique to process the data, and ultimately enabled the mapping of tourist behaviour within the destination. The Royal Albert Dock was used to evaluate the proposed method through video analysis from the six

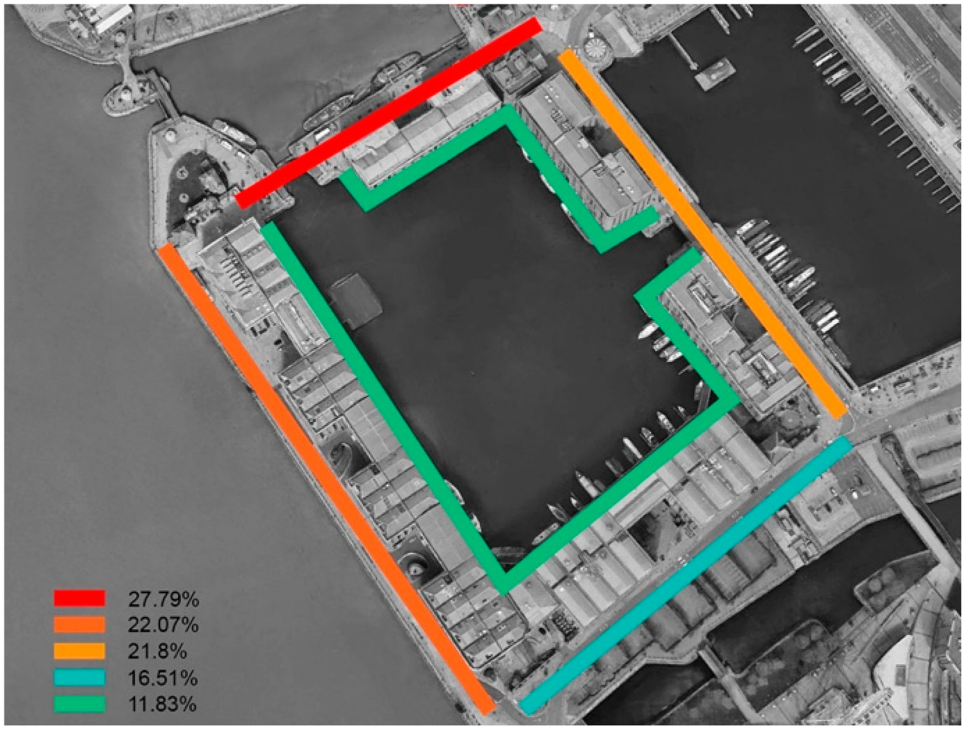

Figure 7. The usage rate for each route.

Table 2. Characteristics of Smart Photo compared to other methods.

Method characteristics	Observation	Interview	Sketching trip on the map	Trip diary	GPS	Digital Footprint	Smart photo
High accuracy					✓	✓	✓
Time-efficient					✓	✓	✓
Cost-efficient	✓	✓	✓	✓		✓	✓
Large sample size					✓	✓	✓
No active visitor participation required						✓	✓
Real-time					✓	✓	✓
Easy to analyse data					✓	✓	✓
Flexible in location	✓	✓	✓	✓	✓		✓

locations resulting in heat maps with tourist distribution data, thus identifying potential problems with the Dock.

The results demonstrate that the proposed method provides a feasible and effective way to map tourist behaviour using image-based processing, which can be extended to other sites using image/video processing. It promises to be a pioneering method for the spatial analysis of movement patterns in outdoor areas.

While the results are promising, several limitations are recognised, and more efforts are needed to improve the method. Firstly, although the accuracy rate for detecting tourists is relatively high (91%), there is still a lack of accuracy. It is challenging to achieve 100% accuracy without manual checking. Secondly, the current method is based on image processing and so it cannot automatically identify the walking direction of each tourist, and it is expected that machine learning can be used in the future to obtain more detailed tourist behaviour.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Xiaochun Zhan holds a BA and MA in Architectural Interior Design. She is currently a Ph.D. student at Liverpool John Moores University. Her research focuses on urban regeneration, particularly culturally oriented research in post-industrial areas, involving the impact of environmental psychology and emotional design on transformation. She has published a number of articles in internationally renowned journals such as the *Journal of Urban Design* and the *Journal of Urban Regeneration and Renewal*. She has also been invited to present her research at major academic symposia in the field of human factors research, such as the International Conference on Human Factors and Applied Ergonomics, and has been published by Springer in conference proceedings.

Fang Bin Guo is a Reader in Industrial Design. He holds BA, MSc, and PhD degrees in industrial design, teaches BSc Product

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Emma Roberts is Associate Dean for Global Engagement for the Faculty of Arts, Professional and Social Studies at Liverpool John Moores University. In addition, she is Reader in History of Art and Design and also Programme Leader and Lecturer in BA (Hons) History of Art and Museum Studies and for the Foundation Year in History of Art and Museum Studies. She completed a Ph.D. on Barbara Hepworth in 1997 (University of Liverpool). Roberts has lectured on all aspects of History of Art and Design for twenty years, and has written five academic books – *Art and the Sea* (2022), *Jamaica Making: The Theresa Roberts Art Collection* (2022), *Who Do You Think You Are? The Asia Triennial Manchester, 2018* (2019), *The Public Sculpture of Cheshire & Merseyside* (2012) and *The Liverpool Academy: A History and Index* (1997) – as well as a number of journal articles and conference papers, and has also curated exhibitions. The focus of Roberts' research lies in three areas: public sculpture; maritime history and design and utopian, 'New Urbanist' architecture and environments.

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