Investigating Spatial Patterns in User-Generated Photographic Datasets by Means of Interactive Visual Analytics

Alexander Kachkaev*
giCentre, City University London

Jo Wood†
giCentre, City University London

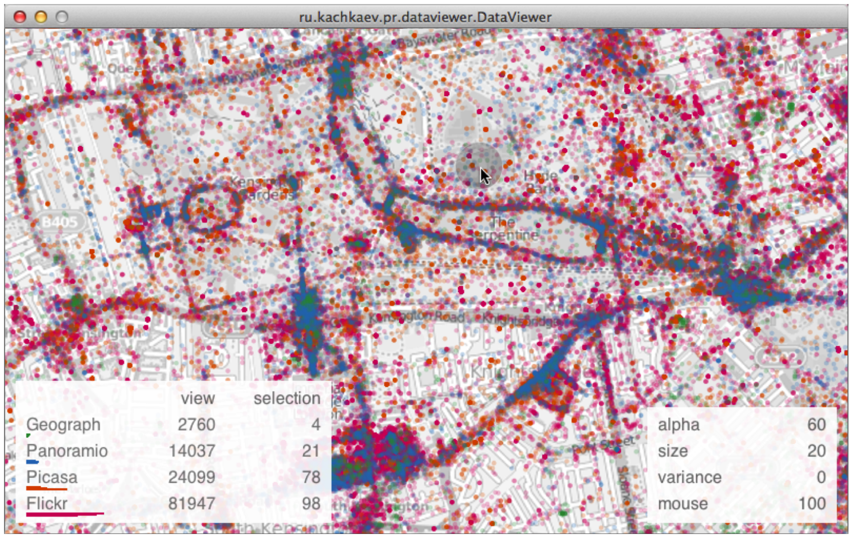

Figure 1: Interface of the visual analytics software tool developed for exploration and assessment of spatial distribution of photographs contributed by users of photo-sharing websites. Four datasets are ordered by number of items within the view and are layered on top of each other. The photographs are represented by semi-transparent circles; relevant statistics is shown in the bottom-left corner.
Background: © CC BY-SA 2.0 OpenStreetMap and contributors.

1 Introduction

Previous research demonstrates that crowd-sourced data available from photo-sharing services has a potential for being a measure of space attractiveness. It has already been used for identifying popular city landmarks and events [5] as well as suggesting tourist trips [7, 6] and even building scenic driving routes [8]. These interesting use cases are based on the observation that the density of geotagged photographs is correlated with the scenicness and popularity of particular places and paths [2]. Developing the idea further, ongoing PhD project is is attempting to introduce an algorithm for generating leisure walks in urban areas, and the analysis of input data is a very important stage of the research process.

Being a result of contributions from thousands of users, spatially distributed crowd-sourced photographic data have a rather complex nature. Photographers share and geotag their images in different ways and for different purposes, and for this reason supposing that a high density of photographs always and straightforwardly corresponds to a popular or an attractive location is perhaps too naive. Therefore, depending on the aims of an algorithm that is using positions of photographs as input, it is necessary to clean initial data from entries that do not match certain criteria.

The complexity of photographic data is accounted by a number of attributes (location, time, title, description, tags, EXIF data, etc.). It lends itself well to a visual analytics approach in order to understand the relevance of photographs to identification of place attractiveness. This paper shows how interactive geovisualization can be helpful for assessing geotagged photographic data for a particular purpose, suggesting and checking filtering methods and revealing hidden dependencies between its attributes and suitability.

Four popular sources of crowdsourced photographic data (Geograph[1], Flickr[2], Panoramio[3] and Picasa Web Albums[4]) are taken into consideration in this research. The datasets have been collected using service APIs for a selected area and contain hundreds of thousands of entries characterised by a number of attributes.

2 Software

Large size of the datasets to explore together with the need of custom-drawn views and interaction formed a number of requirements to the design and the architecture of the visual analytics software tool. The application was developed on Java using Processing[5] and giCentre utilities[6] and is shown in Figure 1. It caches metadata for hundreds of thousands photo entries in memory and allows panning, zooming, toggling layers, changing data representation, applying filtering and displaying statistics in real time. The interface was intentionally left as minimalistic as possible: the entire screen is dedicated to data and control is via keyboard shortcuts and mouse gestures. This enhances cognition and interaction with information [1]. Being launched on a standard contemporary personal computer, the software takes less than a minute to load all four datasets and has a 2GB memory footprint.

*e-mail: alexander.kachkaev.1@city.ac.uk
†e-mail: j.d.wood@city.ac.uk

[1]www.geograph.org.uk
[2]www.flickr.com
[3]www.panoramio.com
[4]www.picasaweb.google.com
[5]www.processing.org
[6]www.gicentre.org/utils

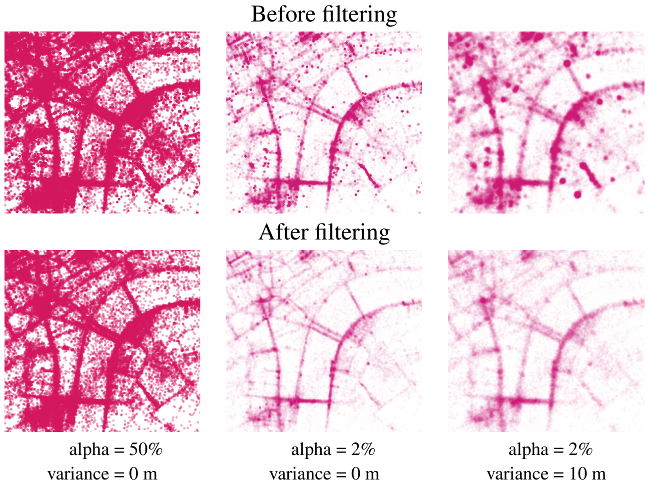

Figure 2: Changing *alpha* (transparency) of circles representing locations of photographs and adding *variance* (a random component with a given standard deviation) to coordinates helps to detect spots containing unreasonably high amounts of photographs and verify absence of such anomalies after filtering. View for Flickr is presented as an example.

3 Detection of Anomalies in the Datasets

Geovizualisation of the photographic datasets helped to reveal a number of issues that could negatively affect the proposed routing algorithm if were left undiscovered [4]. They include:

- locations with large amounts of misplaced photographs caused by errors in data and inaccuracy brought by user interfaces with location search fields;
- uncharted areas due to problems with service APIs;
- uneven temporal distribution caused by events.

4 Verification of Filtering Methods

After potential concerns in the datasets are detected, filtering takes place. This process consists in developing of a set of exclusion rules and marking applicable entries in the database as not accepted. Visual analytics is a very useful instrument during this stage too as it helps seeing the effectiveness of chosen filtering methods and thus plays a role of a feedback function. Figure 2 demonstrates how the software tool has been used to verify that all misplaced photographs are removed by means of comparing the views before and after filtering.

5 Visualisation of Photograph Attributes to Suggest Subject-based Filtering Methods

A photograph is not only characterised by its location – there is a number of related attributes that can tell more about it. As this research is interested only in images taken outdoors, it is important to find the way of excluding as much indoor photography as possible. The same applies to night photography as walking experience during this time different from the day one. It was decided to consider EXIF camera settings that are available for more than 80% of items collected from Flickr and Panoramio including ISO, aperture and shutter speed. A combination of these parameters gives the value of luminance (the amount of light on photographed object) [3]: the more light there is when the photograph is being taken, the more is the probability that it is not the case of dealing with indoor or night photography. Geovisualization of average luminance (Figure 3) reveals quite interesting patterns and shows that Flickr has more locations with high amounts of unwanted items. Filtering in this case requires a threshold or a fuzzy boundary and can be done inaccurately without a prior judgement of photographs by humans. This fact introduces the idea of manual assessment of a sample of photographs to support selection of parameters in further filtering methods and verify their validity. The online survey was implemented for this purpose and is available at www.photoassessment.org.

6 Conclusions and Future Work

Geovisualization of user-generated photographic content was found a very helpful technique for understanding this rather complex and unstructured type of data. Real-time interaction and an ability to change the representation of the datasets allowed to reveal hidden patterns and pitfalls contained in them. Visual analytics software was also successfully used for verification of filtering methods applied on data.

It is planned to take advantage of the geovisualization in future for further data filtering based on the results of the survey and during the process of algorithm implementation, e.g. for assessing calculated weights in the routing graph.

References

[1] J. W. Crampton. Interactivity types in geographic visualization. *Cartography and geographic information science*, 29(2):85–98, 2002.

[2] H. H. Hochmair. Spatial association of geotagged photos with scenic locations. *Geospatial Crossroads@ GI_Forum*, 10:91–100, 2010.

[3] R. Jacobson. *The Manual of Photography: Photographic and Digital Imaging*. Media Manual. Focal Press, 2000.

[4] A. Kachkaev and J. Wood. Using visual analytics to detect problems in datasets collected from photo-sharing services. In *IEEE Conference on Information Visualization (InfoVis)*, 2012.

[5] S. Kisilevich, D. Keim, N. Andrienko, and G. Andrienko. Towards acquisition of semantics of places and events by multi-perspective analysis of geotagged photo collections. *GeoCart*, 2010.

[6] T. Kurashima, T. Iwata, G. Irie, and K. Fujimura. Travel route recommendation using geotagged photos. *Knowledge and Information Systems*, Oct. 2012.

[7] X. Lu, C. Wang, J.-M. Yang, Y. Pang, and L. Zhang. Photo2Trip: generating travel routes from geo-tagged photos for trip planning. page 143. ACM Press, 2010.

[8] Y. Zheng, S. Yan, Z. J. U. N. Zha, Y. Li, X. Zhou, T. A. T. S. Chua, and R. Jain. GPSView: a scenic driving route planner. 2012.

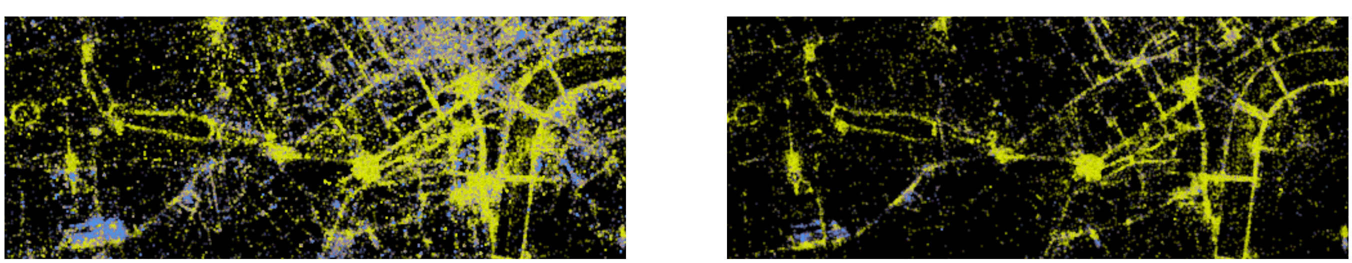

Figure 3: Spacial distribution of average luminance of photographs in two datasets: Flickr *(left)* and Panoramio *(right)*. Lilac coloured locations represent places that are dominated by indoor or night photography, black areas correspond to low numbers of geotagged items.