Affective Route Planning Based on Information Extracted from Location-Based Social Media

Madalina Gugulica, Eva Hauthal, and Dirk Burghardt

Institute of Cartography, TU Dresden, Germany

Research on environmental psychology has shown that humans perceive environments not solely by relating to their physical features but also in reference to their affective qualities. Without regard to the impact these affective perceptions might have on the decision-making process during navigation tasks, most of the current web or mobile pedestrian routing services employ distance or time optimized algorithms and often fail to fully meet the needs of the users. This study wishes to introduce a pragmatic approach of harnessing Location-Based Social Media as a potent and readily available resource for extracting people's affective perceptions of the environment. Furthermore, it proposes a method to aggregate and model the extracted information for the enhancement of pedestrian route planning and identifies the main issues and challenges the nature of these data raises.

Keywords: affective perception; location-based social media content; pedestrian route planning

History: received on 18 July 2019; accepted on 16 August 2019; published on 27 January 2020

1 Introduction

Emotion influences most aspects of cognition and behaviour in the human-space interaction. Hence, humans perceive space and environments not only according to their physical features but also affectively (Bondi et al., 2006; Russell, 2003; Ulrich, 1983). Emotions are a critical aspect of how people experience places (Mody et al., 2009). Thus, capturing and studying the affective meanings people attach to places may lead to a better comprehension of people's spatial experiences and behaviour, as well as to the enhancement of certain location-based services (e.g., navigation systems, travel applications, or urban planning) by offering them a social-context.

In the last decade, numerous researchers have been interested in improving pedestrian navigation systems. Significant progress has been achieved concerning the design of human-centred route planning algorithms to compute more intuitive routes meeting other criteria than just distance and duration. For instance, in order to meet the users' need of simplicity in navigation, Winter (2002) proposed the computation of the 'best' routes in terms of routes with minimal angles and number of turns, while Haque et al. (2007) proposed the calculation of routes minimizing the number of complex intersections with turn ambiguities. Also, the level of safety a user might experience has been the focus of several studies about pedestrian navigation. Miura et al. (2011) consider the illumination of streets to be an important aspect with respect to the level of safety experienced. Similarly, Bao et al. (2017) proposed a pedestrian routing algorithm that considers the street illumination and the width of the sidewalks as significant safety indicators. Recently, Novack et al. (2018) proposed the computation of 'pleasant routes' by quantifying the attractiveness of a route in terms of presence of green areas, social places, and noise. Their customized pedestrian routes are entirely based on OpenStreetMap[1] data.

M Gugulica, E Hauthal, and D Burghardt (2020): *Affective Route Planning Based on Information Extracted from Location-Based Social Media*. In: FB Mocnik and R Westerholt (eds.), Proceedings of the 2nd International Symposium on Platial Information Science (PLATIAL'19), pp. 51–60

https://doi.org/10.5281/zenodo.3628877

PLATIAL'19 Second International Symposium on Platial Information Science (PLATIAL'19)
Coventry, UK; 5–6 September 2019

Most of the approaches aiming to improve route planning for pedestrians are, however, based on objective, physical parameters. To the best of our knowledge, the *AffectRoute* project (Huang et al., 2014) was the first work to acknowledge the importance of considering the subjective relations between people and places to navigation applications. The authors suggest that in order to meet the users' needs concerning safety or attractiveness, people's affective responses to the environment should be integrated in the route computation, which is why they proposed a crowd-sourcing approach to collect the affective information. The results of their empirical evaluation of the algorithm showed that routes ('AffectRoutes') generated considering people's affective perceptions of environments were preferred over the conventional shortest ones. Nevertheless, even with the growing popularity of crowd-sourcing in the era of Web 2.0, collecting enough data for a successful implementation of the routing algorithm at a larger scale was fairly challenging, since this acquisition method requires intense user involvement. Consequently, it is important to find additional meanings of how to collect these subjective data and this is what the present study aims for.

With the increasing use of social media networks (e.g., Twitter[2], Instagram[3], and Flickr[4]) and the dissemination of mobile devices equipped with positioning sensors, Location-Based Social Media (LBSM) data have become a valuable stream of information in environmental and geographical analysis. As a result of the availability, economy and the potential to include more diverse, more detailed, more local, and more contextualized data, mining LBSM data has gained significant attention in the last decade. Topics such as landmarks and movement patterns discovery from geotagged images (Jankowski et al., 2010), place-semantics extraction (Hollenstein and Purves, 2010), context-aware location recommendations (Huang, 2016), studying the people's perception and knowledge of environments (Huang et al., 2013), or extraction of space related emotions (Hauthal and Burghardt, 2016) exemplify some of the research directions this particular type of data has ushered in.

Following the initiated research pathways, this study regards LBSM data, namely the metadata of geotagged Flickr and Instagram images, as a potent and readily available resource for extracting people's affective perceptions of places and environments, and it proposes a methodology to harness these data for pedestrian route planning purposes.

It is important to mention that the methodology treats the affective perceptions in LBSM as taking the shape of linguistic expressions, which are coded with the affective connotations of the words the user chooses to describe the content shared. Moreover, the term *affective perception* encompasses two other concepts, namely *affective response* and *affective quality*. Affective response defines the general internal neuropsychological state of an individual that occurs as an emotional reaction to a single or to various stimuli, while affective quality is the emotion-inducing quality that people verbally attribute to a place, often expressed by describing words such as 'beautiful', 'ugly', 'peaceful', 'hectic', 'boring', etc. (Mehrabian and Russell, 1974). To quantify the affective perceptions, we adopted Russell's dimensional approach (Russell and Pratt, 1980) of classifying and quantifying affective states, which characterizes emotions along two primary dimensions of arousal and valence. Arousal is the extent to which a stimulus is calming or exciting, whereas valence represents the extent to which a stimulus is unpleasant (negative) or pleasant (positive). According to these two perceived dimensions, emotions can be classified by plotting the valence and arousal on the two-dimensional affective space.

2 Approach to Extract and Aggregate the Affective Perceptions

To test the methodology developed, we chose to work with Flickr and Instagram content, since the georeferenced photographs, in most cases, depict places and the information contained in the metadata most likely refer to the captured places. We used metadata (titles, descriptions, tags, and geographical coordinates) attached to Flickr and Instagram images uploaded between 2007 and 2018. The data set comprises 137,421 Flickr and 708,123 Instagram geotagged images located within the boundaries of the city of Dresden.

The approach proposed is based on two assumptions. First, the content that people share on Flickr and Instagram often contains emotional expressions about the transited places, expressions that are not explicit but, rather, coded with affective connotations of the words people choose to describe the content shared. Thus, for instance, a photograph of a place the user perceives as attractive and comfortable would be described and tagged using words with a positive affective connotation (e.g., 'beautiful', 'safe', and 'clean'), whereas the words to describe a less attractive and uncomfortable environment would have a rather negative affective connotation (e.g., 'dirty', 'noisy', and 'desolated'). Secondly, we assume that people often include a place name (e.g., 'Zwinger', 'Frauenkirche', and 'Albertstraße') or a place noun (e.g., 'museum', 'church', or 'street') in the title, description, or set of tags of their content when referring to the perceived environment. The presented approach, in a rather heuristic manner, considers only the metadata that complies with this criterion.[5] To decode the affective perceptions, lexicon-based sentiment analysis was performed on the collected metadata, while a proximity analysis was used to aggregate (in this case, by averaging) the captured affective perceptions in relation to a navigation graph. A detailed description of the conceptual work is presented in the following.

2.1 Data Preprocessing

Location-based social media data come with different levels of positional accuracy depending on the geotagging method that was used. For Flickr, geotags may be retrieved as geographic coordinates from the EXIF (Exchangeable Image File Format) metadata of the image uploaded (if existent), provided by the users either by means of synchronization with track logs from the built-in GPS of their devices or by manually locating photos using a map interface. Flickr stores in the metadata of each geotagged image a location accuracy level ranging from 1 (world level) to 16 (street level), which is automatically assigned depending on the precision of the GPS coordinates or the zoom level of the map used to locate the image. Instagram also offers the users the possibility to geotag their content; however, they are constrained to the selection of the location from a pre-defined list of platial tags hosted by Facebook, which is based on the EXIF location metadata (if available) or the current location of their device. Until August 2015, users were also able to add custom place-labels based on the EXIF metadata coordinates or the device's position. Depending on the geotagging procedure used, a geotagged image does not always provide the exact geographic coordinates of the location from which the image was taken, a fact that leads to a series of issues concerning the positional accuracy and quality of the data. This represents one of the main disadvantages of working with LBSM data and needs to be addressed in future work.

Since the purpose of this work is to integrate the extracted affective responses with a routing graph, a street positional accuracy level is required. Thus, the entries of the data that did not comply with these requirements need to be filtered out. For Flickr data, only geotagged images with a level of positional accuracy higher than 14 or classified under the name 'street' were selected to be further analyzed. Regarding the Instagram data, this process was more complicated due to the lack of information concerning the positional resolution. When searching for a practical solution, we used the platial tags provided by the Instagram API and manually filtered out all the entries with platial tags representing large areas such as the entire city (e.g., 'Dresden') or districts of the city (e.g., 'Loschwitz' and 'Strehlen'). Nevertheless, this solution needs to be revised and improved, because it is based on a rather superficial evaluation of the positional accuracy of the geotagged photos and might lead to inaccuracies in the analysis. In addition, to avoid user-biased valence and arousal values, the metadata generated by a single user at a certain location was merged and duplicates were removed.

Text Normalization, Language Detection, and Hashtags Segmentation. One of the main disadvantages of using LBSM data is that the textual content has a low degree of formal semantic and syntactic accuracy. In order to provide only significant information for the lexicon-based sentiment analysis to be performed, all the hyperlinks, mentions, emoticons, numbers, and other characters besides letters and punctuation were removed. Furthermore, automatic language identification was applied to each entry via the *polyglot*[6] Python library, a natural language pipeline that supports multilingual applications. Very short sentences (< 5 characters) and language predictions of other languages than English and German or with a low confidence (< 0.5) were excluded from the results. According to the language identified, the misspelling and typing errors were corrected using the *pyspellchecker*[7] Python library.

Despite the abundance of noise inherent in social media data, trending hashtags often contain important information and provide insight into the users' affective evaluations of places and environments, and the affective states experienced. Hashtag segmentation is, therefore, an important first step in natural language processing (NLP), since it would be difficult to derive accurate meaning from a piece of text without initially determining the words it consists of. For the extraction of single words from multi-word hashtags, an algorithm was employed that recursively breaks the substrings of the input and searches for the longest matching word in a list of English[8] or German[9] words (depending on the language detected in the former step) until it returns a meaningful phrase.

2.2 Extraction of the Affective Perceptions

To extract the affective perceptions from the metadata of the geotagged images, the lexicon-based sentiment analysis or keywords spotting method was used. Lexicon-based sentiment analysis employs NLP techniques to tokenize, tag the parts-of-speech, and lemmatize text into a list of words, which are further looked up in affective lexicons to determine their valence and arousal values. The approach computes the affective connotation of adjectives and nouns. The reason behind this choice is that while adjectives usually represent the affective qualities of places in adjective-noun constructions (e.g., 'beautiful building', 'quite place', and 'noisy area'), single nouns could also be regarded as an expression of the affective qualities perceived (e.g., 'this place is a ruin', 'the beauty of this area'). Adjectives in verb-adjective constructions (e.g., 'I feel comfortable', 'I feel happy', 'I am scared') represent expressions of affective states as well. The affective connotations of the single words were quantified with values for the dimensions of valence and arousal according to the English affective lexicon created by Warriner et al. (2013) and the BAWL-R (The Berlin Affective Word List Reloaded) German affective lexicon (Võ et al., 2009). The polarity classification of the BAWL-R lexicon was employed, which rates valence on a 7-point scale ranging from -3 (very negative) through 0 (neutral) to +3 (very positive) and arousal on a 5-point scale ranging from 1 (low activation) to 5 (high activation).

In the algorithm developed to preprocess each metadata entry, every single lemmatized word was looked up in the corresponding affective lexicon and, in case it matched one of the lexicon's entries, it was stored in a database together with the corresponding valence and arousal values. Due to the multilingual nature of social media data and the fact that language identification was initially performed at sentence level (for performance reasons – detecting the language of single words has lower levels of accuracy), language identification was performed anew on single words. If the word was identified as belonging to the other language considered and a match in the corresponding lexicon was found, its corresponding affective dimensions as well as the word itself were added to the database. Otherwise, a list of synonyms and hypernyms was generated, and each of them was looked up in the affective lexicon until it matched one of the entries. The word was skipped in case no match was detected. After iterating through all tokens of an entry, the overall affective polarity of the metadata and the average value of the arousal were computed as mean values.

2.3 Aggregation and Modelling of the Affective Perceptions

The basic idea behind this phase is to aggregate the extracted individual affective perceptions, model them as collective affective perceptions, and encode them as a weighting attribute for each street segment of a navigation graph. In this way, the encoded collective affective ratings can be integrated in a typical cost function to compute and deliver routes that consider, apart from physical features such as time and distance, also the affective perceptions towards places and environments.

Spatial Extent of the Affective Perceptions and Aggregation Method. As an aggregation method we propose the computation of the arithmetic mean value of the valence and arousal dimensions of all captured affective perceptions, which are relevantly located with respect to the street segment. In our approach we follow the idea propounded by Pippig et al. (2013) and define the perceptual spatial extent as the idealized space, the features of which could be affectively perceived when located on a specific street segment. Out of practical reasons and in order to enable the implementation of the approach, the proposed methodology regards the perceptual spatial extent as the space represented by the close proximity and limits it to a 100 m buffer area around each street segment. Nevertheless, it is problematic to define a general extent to which a place can be perceived affectively. Further research needs to be conducted in this sense. Since our choice is not based on empirical evidence, we applied the same reasoning on which the Inverse Distance Interpolation method is based. Accordingly, we assume each affective perception extracted to have a local influence that diminishes with distance. Consequently, in the computation of the arithmetic mean value of the valence and arousal values for each street segment, the discrete values closest to the street segments receive greater weights. The weights diminish as a function of distance.

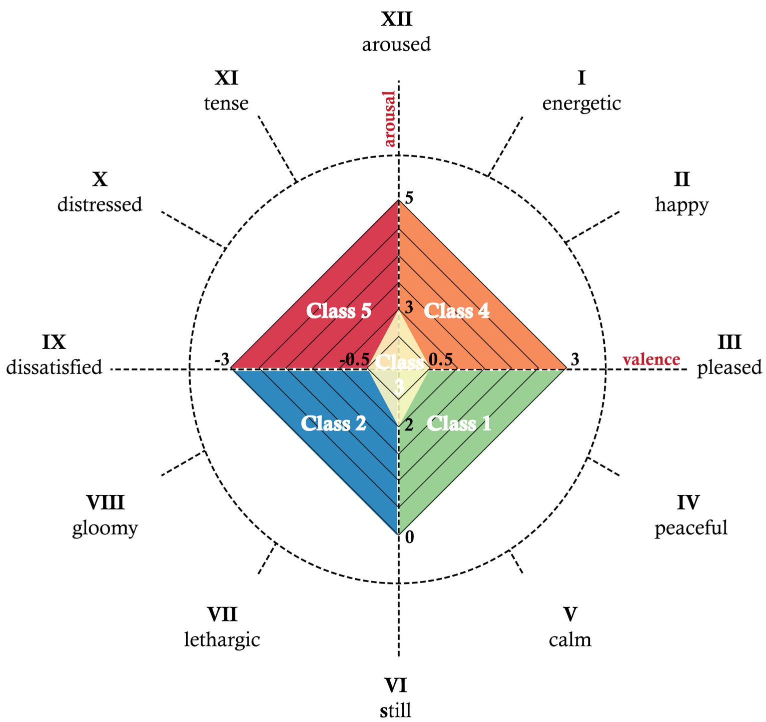

Figure 1: Five affective classes. Adapted from the 12-point circumplex structure of the core affect (Yik et al., 2011, p. 706)

Quantification and Modelling of the Affective Perceptions. For the quantification and classification of the affective ratings, we applied a bipolar framework that is organized around the dimensions of valence and arousal and is largely based on the circumplex model of affect (Russell and Pratt, 1980). The framework employs a single bipolar scale ranging from positive to negative to measure the subjective valence. The changes in reported valence are subjectively different from the changes in the reported arousal. Therefore, this framework also employs an additional arousal scale ranging from low (sleepy/inactive) to high (excited/active). As can be observed in Figure 1, the different emotional states can be represented at any level of valence and arousal, or at a neutral level of one or both of these factors. In order to classify the extracted affective perceptions by following the same principle, five possible affective classes were conceptualized as follows:

1. *Positive valence and low arousal affective class (valence* > 0.5 *and arousal* < 2.5*).* In this case the affective responses could reflect a pleasant, comfortable, calm, or attractive environment such as gardens or parks.

2. *Negative valence and low arousal affective class (valence* < -0.5 *and arousal* < 2.5*).* This class represents places that evoke sentiments of sadness and dissatisfaction. For example, war memorials or places associated with sad events.

3. *Neutral valence and neutral arousal affective class (*$-0.5 \leq$ *valence* ≤ 0.5 *and* $2 \leq$ *arousal* ≤ 3*).* Due to the numerous affective ratings that have slightly positive or negative connotations (values between 0 and ± 0.5), this approach proposes the mentioned interval $[-0.5, 0.5]$ as neutral valence values. Moreover, it was observed that most of the affective responses that fall in the category of neutral valence have arousal values between 2 and 3. This class includes rather ordinary places that do not particularly activate pedestrians affectively. An example of such an environment could be represented as common residential areas.

4. *Positive valence and high arousal affective class (valence* > 0.5 *and arousal* > 2.5*).* This would be the case of energetic and pleasant places, such as busy touristic areas of a city, sport centres, and shopping areas.

5. *Negative valence and high arousal affective class (valence < −0.5 and arousal > 2.5).* This class is representative for areas and places that evoke feelings of fear, terror or, generally, a high level of discomfort. Some examples could be represented by infamous suburbs where the rate of criminality is high, sites of unpleasant events such as attacks and revolts, or noisy areas with intensive traffic.

3 Results

To test the methodology described, an algorithm was developed and tested on the trial data. Consequently, 243,882 individual affective perceptions, which were generated by 98,560 distinct users, could be captured. The visualization of the affective perceptions (see Figure 2) revealed one of the main issues LBSM data raise, namely the irregular spatial distribution of the users' contributions caused by the popularity bias. Thus, data peaks emerge in central areas and highly frequented tourist hot-spots, while peripheral or less frequented areas are marginalized.

Before classifying the individual affective perceptions extracted and in order to ensure the validity of the classes conceived, five lists of prevailing words for each of them were created. Inspecting the word lists, the presence of a relatively high number of representative affective terms confirmed that the valence and arousal values ranges chosen were suitable. The classification results showed that most of the extracted affective ratings (71% of the total) belong to the *positive valence and low arousal affective class*. The second most prevalent affective class (with 19%) was the one represented by neutral valence and arousal values, while the other three classes summed up a total of just 8% of the whole

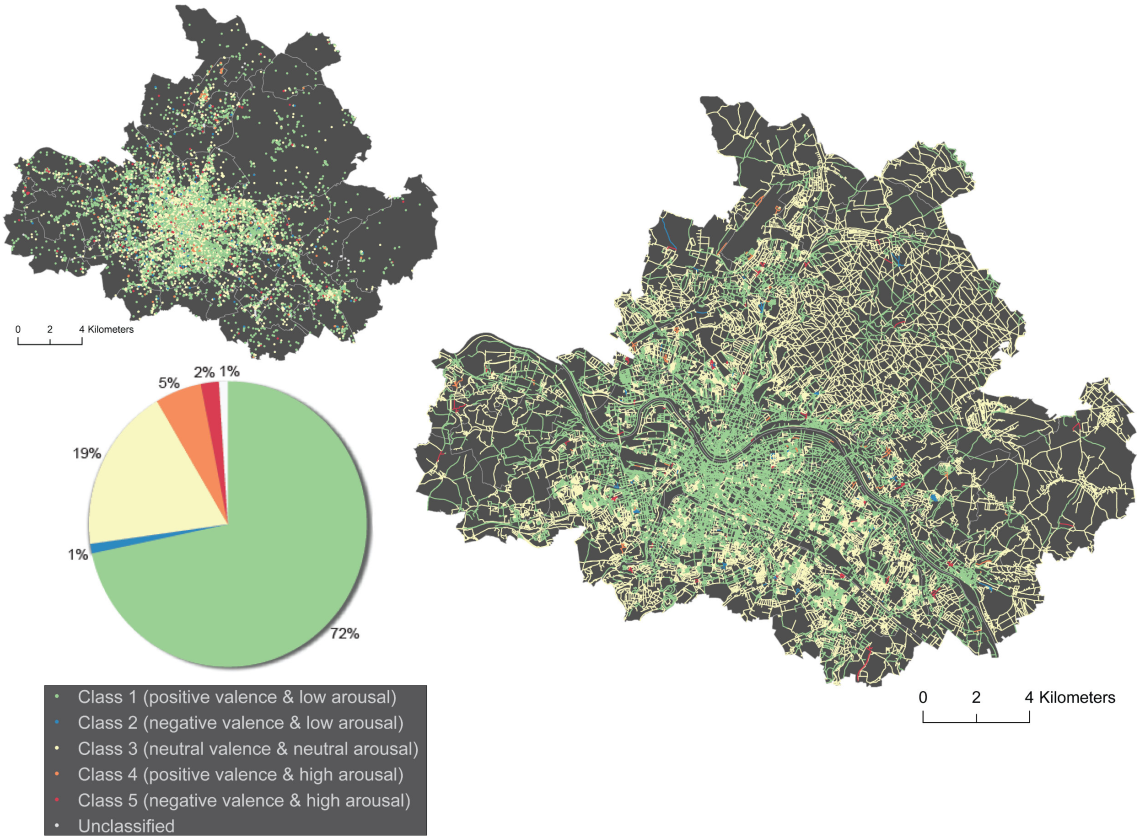

Figure 2: Classification of the street segments according to the extracted affective perceptions. The visualization of the classified extracted affective perceptions (left map) reveals an irregular spatial distribution as well as an uneven distribution of the classes. The impact of these results on the classification of the street segments (right map) is twofold: 40% of the street segments got assigned a local average valence and arousal due to the sparsity of the identified affective perceptions and over 50% of the street segments are characterized by positive valence and low arousal.

extracted affective perceptions and 2% remained unclassified – the ranges selected for the classification not covering their affective dimensions. This might indicate that social media users have a general tendency to share content with a positive or neutral affective association, such as pictures of popular, pleasant places that evoke positive emotions, or images that depict common environments encountered on a daily basis, such as the areas where the users live, work, or study.

The classification of the street segments, according to the aggregated collective ratings, follows the same trend. More than half of the edges of the graph have been assigned positive valence and low arousal weights. At a small difference, the next class that comprises a large part of the edges is represented by the *Neutral valence and arousal affective class* (nearly 49% of the network). However, the data sparsity issue also has repercussions on the classification of the street segments. While some of the streets have been associated numerous affective ratings, some others have no associated ratings at all and get assigned a local average valence and arousal of all the affective perceptions identified in the corresponding district. Thus, only for 10% of the edges, the aggregated valence and arousal values rely on the discrete affective perceptions. For almost 40% of the street segments, there were no data available. The other three affective classes are representative for less than 1% of network, whereas 0.36% of the edges remain unclassified because the valence and arousal values do not fall within any of the proposed intervals.

4 Discussion and Conclusion

Throughout the conducted research a considerable number of issues and difficulties concerning the nature of LBSM data could be identified. The first issue encountered was related to the language processing. In the interest of evaluating the developed algorithm, we tested it separately on a set of 100 randomly selected images while closely monitoring each step of the execution. Out of the 700 hashtags detected (492 English and 208 German), 208 were segmented incorrectly. Over 50% of the incorrect segmentation occurred due to mixed languages usage and, consequently, erroneous language identification. Furthermore, the algorithm identified in total 857 words (656 English and 201 German words) that could represent an affective state or quality. Only 462 words (or their corresponding synonyms or hypernyms) matched an entry in one of the affective lexicons. In total, 40 words were German words misclassified as English and 64 words were English words misclassified as German. Thus, the implications of the erroneous language processing on the extraction of affective perceptions from the metadata of geotagged photographs were twofold. Due to incorrect language detection, on one hand, the hashtags segmentation algorithm performed erroneously. On the other hand, the computation of the valence and arousal scores was not possible. The improvement of language detection is a challenging task due to the multilingual nature of texts. Nevertheless, to maximize the performance of the sentiment analysis, these issues need to be further studied and better language detection strategies should be applied, which will be part of the future work planned.

Moreover, the proposed approach only considers metadata entries that refer to specific places situated in the study area, and it assumes that, as long as the content's metadata includes a toponym, affective responses towards that place or its affective qualities are expressed. However, this assumption is not sustained by empirical evidence and represents an expedient approach to the matter. A possible improvement of the methodology concerning this aspect is represented by the employment of topic modelling tools to discover the topics that occur in the LBSM content. This is regarded as future work as well.

With reference to the aggregation of the extracted affective ratings, two possible limitations of the approach need to be addressed. First, the proposed approach assumes that affective responses from a large number of users can be aggregated (averaged) to approximate the collective affective evaluation of the area surrounding one specific street segment. Notwithstanding, people's affective responses to environments are subjective in nature and abstract values. Consequently, it is unclear to what extent averaging abstract subjective data is suitable for the identification of collective affective perceptions. This aspect should be subject to further investigations. Secondly, to enable the implementation of the approach and following the idea of a perceptual spatial extent, the affective responses located within a radius of 100 m surrounding each street segment were considered as influential in the calculation of the valence and arousal values of the collective affective ratings. Nevertheless, this aspect needs to be revised since the choice is not based on empirical evidence and might lead to further data validity issues. In addition to these limitations of the study, utilizing LBSM data in research requires constant contemplation upon further data quality issues, such as positional accuracy, or privacy concerns.

To conclude, the conducted research lays out the main issues to be considered when working with LBSM data and presents a fairly solid methodological framework to extract affective information from textual metadata of images shared on Instagram and Flickr. The study also provides new lines of evidence regarding the selectivity bias in terms of places' popularity and the general tendency of social media users to share content with a rather positive affective connotation. Moreover, despite the numerous quality issues identified, on account of the great number of affective perceptions captured, it can be asserted that LBSM data represent a significant source to be regarded in the collection of affective information. We suggest that, for the development of human-centred route planning algorithms, LBSM data could be considered as a weighty additional source to fill in the gaps in the traditionally acquired or crowd-sourced data sets.

Notes

1. http://openstreetmap.org
2. http://www.twitter.com
3. http://www.instagram.com
4. http://www.flickr.com
5. In the interest of filtering out the entries that are not related to places or perceived environments, a rudimentary version of a gazetteer was compiled by creating a list of the toponyms (both in English and German) associated with the study area. The gazetteer (a collection of street and district names, points of interest, land use categories, amenities, and places of worship) containing 18,863 entries was compiled gathering data from OpenStreetMap, Geonames, and Wikitravel.
6. https://pypi.org/project/polyglot/
7. https://pypi.org/project/pyspellchecker/
8. The English collection of words contains 127,156 entries and was assembled by combining the WordNet (https://wordnet.princeton.edu) lexical database (a database of English nouns, verbs, adjectives, and adverbs that are grouped into sets of cognitive synonyms) with the gazetteer compiled for placename identification.
9. For the compilation of the German word list, the same gazetteer was merged with a list of German words with slightly more than 1.9 million entries available online and created by Jan Schreiber in 2017 (https://sourceforge.net/projects/germandict).

Acknowledgements

We would like to thank Dr.-Ing. A Dunkel for providing the Flickr and Instagram data necessary for the implementation of the methodology developed.

ORCID

Eva Hauthal https://orcid.org/0000-0001-8917-600X
Dirk Burghardt https://orcid.org/0000-0003-2949-4887

References

Bao, Siya; Nitta, Tomoyuki; Yanagisawa, Masao; and Togawa, Nozomu: *A safe and comprehensive route finding algorithm for pedestrians based on lighting and landmark conditions*. IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, E100.A(11), 2017, 2439–2450. doi: 10.1587/transfun.E100.A.2439

Bondi, Liz; Davidson, Joyce; and Smith, Mick: *Introduction: geography's 'emotional turn'*. In: Davidson, Joyce; Bondi, Liz; and Smith, Mick (eds.), *Emotional Geographies*, London, UK: Routledge, 2006. 1–16. doi: 10.4324/9781315579245

Haque, Shazia; Kulik, Lars; and Klippel, Alexander: *Algorithms for reliable navigation and wayfinding*. Proceedings of the 2006 International Conference on Spatial Cognition V: Reasoning, Action, Interaction, 2007, 308–326

Hauthal, Eva and Burghardt, Dirk: *Mapping space-related emotions out of user-generated photo metadata considering grammatical issues*. The Cartographic Journal, 53(1), 2016, 78–90. doi: 10.1179/1743277414Y.0000000094

Hollenstein, Livia and Purves, Ross: *Exploring place through user-generated content: using Flickr tags to describe city cores*. Journal of Spatial Information Science, 1, 2010, 21–48. doi: 10.5311/JOSIS.2010.1.3

Huang, Haosheng; Klettner, Silvia; Schmidt, Manuela; et al.: *Affectroute–considering people's affective responses to environments for enhancing route-planning services*. International Journal of Geographical Information Science, 28(12), 2014, 2456–2473. doi: 10.1080/13658816.2014.931585

Huang, Hoasheng: *Context-aware location recommendation using geotagged photos in social media*. ISPRS International Journal of Geo-Information, 5(11), 2016, 195. doi: 10.3390/ijgi5110195

Huang, Hoasheng; Gartner, Georg; and Turdean, Timea: *Social media data as a source for studying people's perception and knowledge of environments*. Mitteilungen der Österreichischen Geographischen Gesellschaft, 155, 2013, 291–302. doi: 10.1553/moegg155s291

Jankowski, Piotr; Andrienko, Natalia; Andrienko, Gennady; and Kisilevich, Slava: *Discovering landmark preferences and movement patterns from photo postings*. Transactions in GIS, 14(6), 2010, 833–852. doi: 10.1111/j.1467-9671.2010.01235.x

Mehrabian, Albert and Russell, James A: *An approach to environmental psychology*. Cambridge, MA, USA: MIT Press, 1974

Miura, Hirokazu; Takeshima, Syujo; Matsuda, Noriyuki; and Taki, Hirokazu: *A study on navigation system for pedestrians based on street illuminations*. 2011, 49–55. doi: 10.1007/978-3-642-23854-3_6

Mody, Ruturaj N; Willis, Katharine S; and Kerstein, Roland: *WiMo: location-based emotion tagging*. 2009, 14. doi: 10.1145/1658550.1658564

Novack, Tessio; Wang, Zhiyong; and Zipf, Alexander: *A system for generating customized pleasant pedestrian routes based on OpenStreetMap data*. Sensors, 18(11), 2018, 3794. doi: 10.3390/s18113794

Pippig, Karsten; Burghardt, Dirk; and Pretchtel, Nikolas: *Semantic similarity analysis of user-generated content for theme-based route planning*. Journal of Location Based Services, 7(4), 2013, 223–245. doi: 10.1080/17489725.2013.804214

Russell, James A: *Core affect and the psychological construction of emotion*. Psychological Review, 110(1), 2003, 145–172. doi: 10.1037/0033-295X.110.1.145

Russell, James A and Pratt, Geraldine: *A description of the affective quality attributed to environments*. Journal of Personality and Social Psychology, 38(2), 1980, 311–322. doi: 10.1037/0022-3514.38.2.311

Ulrich, Roger S: *Aestethic and affective response to natural environment*. In: Altman, Irwin and Wohlwill, Joachim F (eds.), *Behavior and the Natural Environment*, Boston, MA, USA: Springer, 1983. 85–125. doi: 10.1007/978-1-4613-3539-9_4

Võ, Melissa LH; Conrad, Markus; Kuchinke, Lars; et al.: *The Berlin affective word list reloaded (BAWL-R)*. Behavior Research Methods, 41(2), 2009, 534–538. doi: 10.3758/BRM.41.2.534

Warriner, Amy Beth; Kuperman, Victor; and Brysbaert, Marc: *Norms of valence, arousal, and dominance for 13,915 English lemmas*. Behavior Research Methods, 45(4), 2013, 1191–1207. doi: 10.3758/s13428-012-0314-x

Winter, Stephan: *Modeling costs of turns in route planning*. Geoinformatica, 6(4), 2002, 345–361. doi: 10.1023/A:1020853410145

Yik, Michelle; Russell, James A; and Steiger, James H: *A 12-point circumplex structure of core affect*. Emotion, 11(4), 2011, 705–731. doi: 10.1037/a0023980