GIS-Based Emotional Computing

Subjects: Others
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In recent years, with the growing accessibility of abundant contextual emotion information, which is benefited by the numerous georeferenced user-generated content and the maturity of artificial intelligence (AI)-based emotional computing technics, the emotion layer of human–environment relationship is proposed for enriching traditional methods of various related disciplines such as urban planning. This paper proposes the geographic information system (GIS)-based emotional computing concept, which is a novel framework for applying GIS methods to collective human emotion. The methodology presented in this paper consists of three key steps: (1) collecting georeferenced data containing emotion and environment information such as social media and official sites, (2) detecting emotions using AI-based emotional computing technics such as natural language processing (NLP) and computer vision (CV), and (3) visualizing and analyzing the spatiotemporal patterns with GIS tools. This methodology is a great synergy of multidisciplinary cutting-edge techniques, such as GIScience, sociology, and computer science. Moreover, it can effectively and deeply explore the connection between people and their surroundings with the help of GIS methods. Generally, the framework provides a standard workflow to calculate and analyze the new information layer for researchers, in which a measured human-centric perspective onto the environment is possible.

Keywords: human–environment relationship ; collective emotion ; GIS-based emotional computing

1. Introduction

The human–environment relationship has always been a key issue in geography in terms of the interaction between human society and its activities and geographical environment[1][2][3]. There is a significant body of literature that investigates such relationship from various aspects, including evaluation[4], modeling[5], and application[6], and these studies provide a solid foundation for the burgeoning and interdisciplinary fields, such as quality of life (QOL)[7].

Presently, there are two main forms to measure the interaction between human and environment: the objective indices of environment attributes, such as evaluation index systems, and the subjective indices from human perceptions, such as sense of place. As for the former, the evaluation index systems usually are composed of indices that cover aspects such as accessibility, density, land use, and land cover changes, and economics[8][9]. Nevertheless, the selection of such indices is limited to current understanding of the interaction between humans and environment. In other words, human–environment relationship may be underrepresented with such methodology. As for the latter, the literature delivered various questionnaires to obtain indigenous people’s sense of place in three place constructs: place identity, place dependence, and place attachment[10]. Although subjective indices like sense of place seem to draw a synthetical picture of human–environment relationship from the humanistic perspective, they emphasize portraying people’s abstract emotional connection with their inhabited locality. Similarly, the items of questionnaires are still constrained by the state of knowledge.

On the one hand, the concept of “place” is more than a location or a restricted space but a reality to be understood from the perspectives of people. “Place” reflects the way people perceive and experience the surrounding environment[11]. On the other hand, emotion, which dramatically influences human consciousness [12], serves as a bridge between the environment (both physical and social environment) and the final experience that a person obtained from the environment[13][14][15][16][17]. Therefore, exploring collective emotion of places plays a conspicuous role in human–environment relationship research. With the advent of big data era and the maturity of artificial intelligence (AI)-based emotional computing techniques, massive individual-level emotional information is available to scientists. Over the last decade, emotional computing has gained momentum, and it provides possibilities for developing a new layer of emotion information for human–environment relationship research.

In this paper, we present a novel research framework, which equips collective emotion with geographic information system (GIS) methods to quantitatively measure the emotion layer of human–environment relationship, namely GIS-based emotional computing. This framework aims to provide a standard workflow for calculating and analyzing the new information layer in different geographical granularities. These results allow further study about understanding human behavior in a certain environment and planning from a human-centric perspective. Crucially, we expect that this framework provides complementary information to existing methodologies, rather than supplant them (see Figure 1). We define the term GIS-based emotional computing as a data-driven methodology that extracts emotional characteristics in places and analyzes it with GIS methods. Compared to affective computing proposed by Picard[18], GIS-based emotional computing focuses on collective emotion in places rather than individual emotional states. We advocate that the GIS-based emotional computing can be a prominent research framework, and a useful tool, for dynamic diagnosis of the human–environment relationship in different geographical and temporal granularities, with collective emotions obtained from on-the-fly user-generated contents (UGCs).

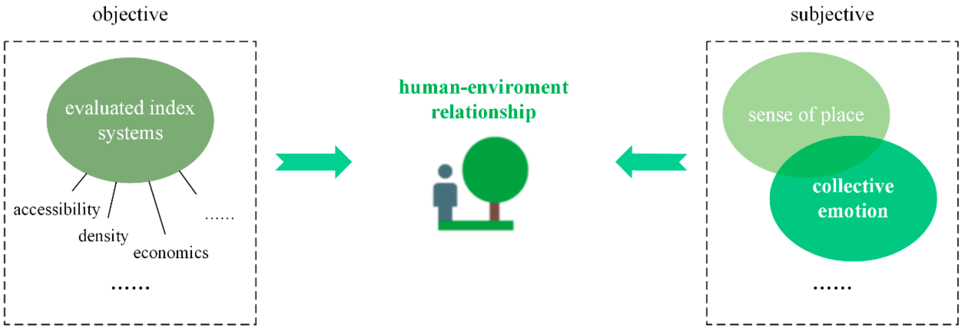


Figure 1. The methodologies of quantitatively and qualitatively describing human–environment relationship.

As illustrated in Figure 2, the framework comprises three key steps: first, collecting environment and emotion related data in various context from data sources such as social network sites and official sites; second, exploring and cleaning data and extracting emotional information from georeferenced emotion related data based on its data structure; and third, conducting spatiotemporal analysis using GIS methods such as spatial interpolation and kernel density analysis in order to provide researchers with additional insights into the complex human–environment relationship.

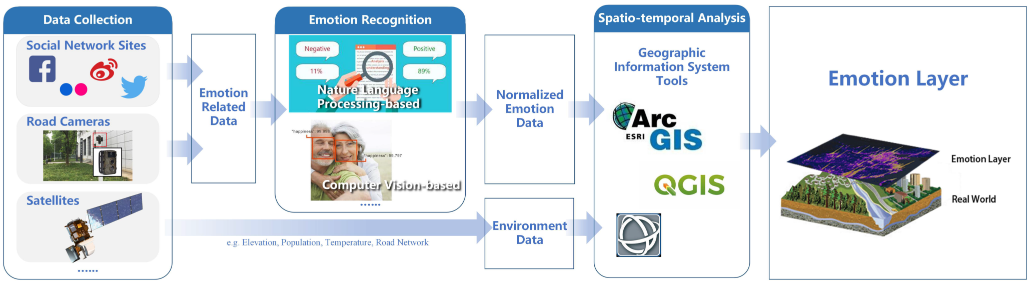
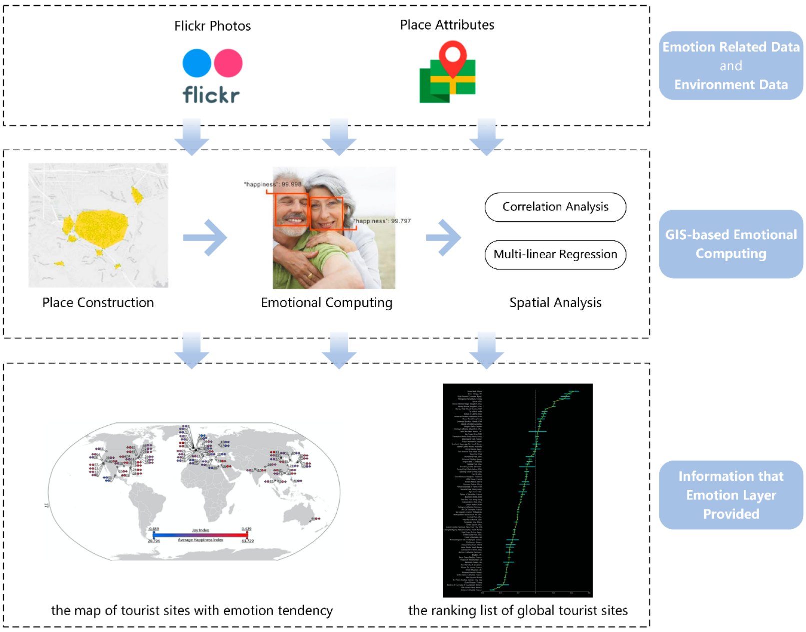


Figure 2. The conceptual framework of geographic information system (GIS)-based emotional computing.

2. Example of Implementing GIS-Based Emotional Computing

The emotion information analyzed by GIS-based emotional computing plays an increasingly vital role in human–environment relationship research, and it serves as a critical component of various applications including resource management, conservation, human geography, crime analysis, real estate, psychology, environmental justice, etc. Hereby we give an example that exhibits the potential to quantify human emotion and serves as a layer in GIS for human–environment relationships study.

The recommendation of tourist sites is a key topic in tourism studies. With GIS-based emotional computing techniques, georeferenced contents uploaded by tourists to photo services in the public domain enrich traditional recommendation systems with an emotion layer. One of our previous studies collected Flickr photos of 80 tourist sites all over the world, and applied spatial clustering to emotion information extracted from photos, for constructing an emotion layer for these tourist sites. Afterward, a map of tourist sites with emotion tendency and a ranking list of global tourist sites based on emotion were drawn, which serve as references for potential tourists. By calculating and analyzing the emotion layer and other layers in GIS, we have also attempted to identify, which natural and non-natural environmental factors may have an impact on visitor’s emotions[19]. The workflow of the example can be seen in Figure 3. This example illustrated that, with GIS-based emotional computing, it is possible to cater to tourist preferences for accurate advertising and management of the tourist industry.



redraw from Kang Y, et al. [84]

Figure 3. The workflow of an example implementing GIS-based emotional computing.

3. Conclusions

In this paper, authors propose a new conceptual framework: GIS-based emotional computing, for providing a new approach to measure the emotion layer of human–environment relationship. The methodology comprises three steps: (1) collecting environment and emotion related data from different data sources, (2) detecting emotional information from georeferenced emotion related data by AI-based emotional computing techniques, and (3) conducting spatiotemporal analysis using GIS. The current literature related to each step was reviewed, and the improvements of GIS-based emotional computing can be done were discussed. The emotion layer reveals deep interactions between human and their surrounding environment, and it reveals "what people real feel" instead of "what people would feel". GIS-based emotional computing consolidates the cutting-edge technologies of multidisciplinary, such as GIScience, sociology, and computer science, for providing a more effective and accurate avenue to calculate and analyze the emotion layer. It is important to note that GIS-based emotional computing of this scope has only been possible recently, due to the increasing capability of both massive UGC with emotional information and the technologies that take advantage of these resources. This implied that GIS-based emotional computing may have unlimited potential because of developing and advancing technologies. However, while the promise of collective emotion in describing the human–environment relationship is alluring, the challenges above have to be addressed for increased uptake of GIS-based emotional computing.

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