Who are happier? Spatio -temporal Analysis of Worldwide Human Emotion Based on Geo-Crowdsourcing Faces

Yuhao Kang, Xiaohuan Zeng, Zimo Zhang, Yueyao Wang, Teng Fei*
School of Resource and Environmental Sciences
Wuhan University
No.129 Luoyu Road, Wuhan, China, 430079
{kkyyhh96, zengxh, zhangzimo, gis_wyy16, feiteng}@whu.edu.cn

***Abstract*—Geotagged social media data provides unprecedented opportunities and meaningful aspects of human analysis in the era of volunteered geographic information (VGI). Previous studies have examined users' emotions shared on these media, while most of them focus on text-based data and ignore diverse images. In this paper, we used a huge global scale image dataset: YFCC100, to extract emotions from photos and to describe the worldwide geographic patterns of human happiness. Two indices of Average Smiling Index (ASI) and Happiness Index (HI) are defined from different perspectives. We computed the spatio-temporal characteristics of facial expression-based happiness from a global scale and linked them to some demographic variables (ethnicity, gender, age, time and nationality). After that, the robust analysis was made to ensure our results are reliable. Results are in accordance with some previous studies and our common sense, for example, White and Black are better at expressing happiness than Asian, women are more expressive than men, and happiness expressed varies across space and time. Our research provides a novel methodology for emotion measurement and it could be utilized for assessing a region's emotion conditions based on geo-crowdsourcing data. Robust analysis results on our dataset indicate that our approaches are reliable and could be implemented in research of human emotions.**

Keywords—geospatial crowdsourcing; affective computing; cognitive recognition; social sensing; face detection; volunteered geographic information.

I. INTRODUCTION

Human emotions and cognition are innate and can expand our understanding of human behavior [1]. For a long time, researchers from psychology, sociology, economics, and politics have paid attention to human perceptions of their environment and lives [2]. The traditional methods of emotional measurement are based on self-evaluation, survey and physiological index tests. The annual World Happiness Report generated by the United Nations Sustainable Development Solutions Network ranks happiness of countries based on social and cultural attributes. The Gross National Happiness (GNH) aims at measuring the collective happiness in any specific nation from a socio-economic perspective. The Satisfaction With Life (SWL) test accomplished by administering questionnaires could effectively reflect an individual's feelings of life [3]. However, traditional researches aforementioned have internal drawbacks. They need a large expense of manpower, time and money [4]. In addition, results could not provide real-time insight since they are restricted by the sampling frequency of time and population [5], [6].

That is now changing. With the appearance of online social network platforms, volunteered geographic information (VGI) provides new insights and methods to help social scientists study individual behaviors in space and time as a complementary of the traditional measurements [7]. Spatial data generated by users can be shared through Web 2.0 portals [8], which means each individual can create, assemble, and disseminate geographic information to play as a sensor of our environment [9]. People voluntarily provide information, as an important source of data for geographic information research.

The public generates huge amounts of social media data on the Internet every second. Content shared on social networks reveals users' perception of their environment surrounded, daily life condition, and most importantly, their emotions inadvertently, which is valuable for analyzing the relationships between human behaviors and emotions. In particular, a large proportion of such data have accurate geo-information. Thus, in the era of big data, we have the opportunity to take a look at the big picture of the spatio-temporal characters of human emotion at a global scale based on the crowdsourcing geographical data.

Recent studies have continuously explored the spatial characteristics of human emotion from various data sources, such as blogs, Twitter, Facebook, with advanced technology in artificial intelligence and computer vision. Scholars have applied Natural Language Processing (NLP) techniques to extract emotions for analysis and gained excellent results. Twitter provides opportunities for the analysis of mood from a spatio-temporal perspective [10]. Bollen et al. extended the psychometric measurement Profile of Mood States (POMS) to infer sentiment from tweets [11]. Dodds et al. provided a novel method [12] and Mitchell used this to extract emotion from Twitter public stream [13] and generated an emotion distribution map of the USA. Bandhakavi et al. used lexicon based feature extraction to classify text according to emotion from the news, Twitter, blogs and incident reports [14].

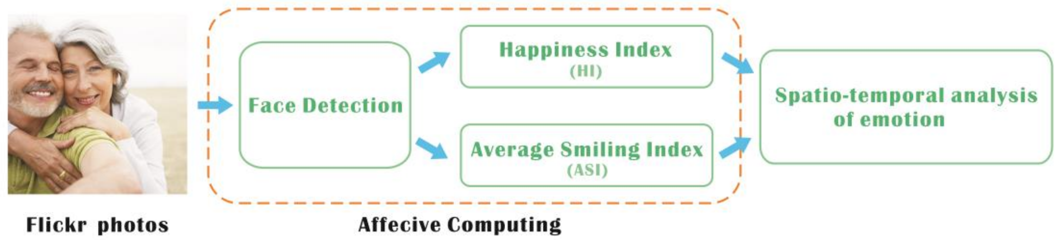

Figure 1 Framework for Analyzing Emotion Distribution

Kramer et al. once built a sentiment metric according to status update on Facebook and aggregate the metric at national US level to compare with the SWL test [15]. An online platform called Felicitta is generated to visualize happiness status in the Italian cities based on Twitter data [16]. Mature applications have been created using word-based and sentence-based emotion measurement.

Compared to the popularity of the text-based emotion measurement, another valuable dataset: image, and image-based emotion analysis, has fallen far behind though both of them develop in parallel. The majority of researches about image-based emotion extraction focus on emotional annotations on images [17], which are still text-based methods while just change the data source. Borth et al. proposed an approach to understand the visual concepts in images related to sentiments and built a novel application SentiBank for affective computing [18]. Joshi et al. built a framework which can infer emotion from digital images automatically [19]. However, the majority of the data, that is the image content itself, which could have contained abundant information about human emotions, is absent from analyzing.

Nowadays, human's rich facial expressions can be detected from photos and could be applied in emotion analysis. In reality, extensive researches have examined the relationship between facial expressions and emotions and pointed out that facial expressions can be indicative of an individual's emotional status, social conditions, future development and other personal developments [20]–[23]. Facial expressions can be divided into several basic emotions [24]. For example, the Darwin's six kinds' classification: anger, disgust, happiness, fear, sadness, and surprise [25]. Another finer grained division methods, Ekman's Facial Action Coding System is a widely used example and is used in many studies [26]–[28]. Meanwhile, with the development of information technology, photos are increasingly being used to record facial expressions. The mature application of face recognition technology makes it possible to use photos to recognize facial expressions and give each face a specific score to better quantify the emotion information [29]. More importantly, compared with the text analysis, photos can avoid cultural and language restrictions [30]. Research has shown that the expressions of similar emotions and facial expressions are similar all over the world [31].

Noticing this opportunity and necessity to utilize this precious dataset learning about human emotions, some scholars have focused on emotion measurement based on facial expression. Abdullah et al. [32] used photos from Twitter to monitor human smile and proved that emotion extracted from photos can provide meaningful information. Kang et al. [33] have examined the relationship between emotions in Manhattan and the stock index based on cognitive computing. However, few researches have mined the geographic patterns of human emotions at global scale based on facial expression detection of crowdsourcing content. Considering that the race, age, nationality and some other demographic attributes are all from a point view of the large crowd, we believe that a large-scale human emotion detection and analysis could provide insights on the background values of human emotion and its distribution, in a statistical sense.

In this paper, we attempt to explore the spatio-temporal characteristics of human emotion based on the geospatial crowdsourcing content. Considering that happiness is the most important part of life quality, we would like to know where and who are happier, therefore we only focus on human's happiness in this research. We specifically aim at: (1) developing a computational model for assessing and describing the emotion in a specific region from geo-crowdsourcing faces; (2) characterizing the geographical and temporal pattern of emotion from a large worldwide scale. We will pay a revisit of the questions below through collected emotion: People in which countries are happier than others? Are women happier than men according to prior researches [31]? Are Asian as happy as Black and White [34]? And we will compare our results with researches based on other data sources.

II. METHODOLOGY

Figure 1 shows the whole phases of our methodology framework. Firstly, we collect the photos from Flickr and get the location information of each photo. Then human faces are detected via a computer-vision based platform called Face++. If an image is detected as having faces, emotions will be extracted and calculated with a set of scores for determining the degree of the human mood, which we call as affective computing. Then, we employed two indices to measure the emotions in our dataset. This model is used to explore the relationship between the emotion and some other demographic attributes then. Finally, we analyze the emotion in a specific region for a certain time to characterize the spatio-temporal distribution of emotion.

A. Data Preparation

In this research, we utilized YFCC100 dataset released by Yahoo Webscope program [35]. YFCC100 is the largest public social media dataset that can be downloaded so far with 100 million photos and videos from 2004 to 2014. Each photo in the dataset contains object identifier, user identifier, timestamp, location information (coordinates), geotags and other attributes.

Photos without location information were discarded at first since we cannot position them. The spatial distribution of all these photos was mapped by Datashader using Python 3 for visualization under Web Mercator projection. 48,469,203 photos remained after we discarded photos without location information in our research.

B. Affective Computing

In order to extract human emotions from photos, we utilized Face++ platform (https://www.faceplusplus.com/), a cloud vision services platform that provides a complete set of visual technology services for facial analysis and recognition. Two emotion-related scores can be acquired using Face++'s API. The first one is called Smile Face (SF), which consists of a smiling threshold and a smiling value, stating whether it is a smiling face and the smiling degree. When the smiling value is greater than the threshold (30.1), this face is judged as a smiling face. The higher the value is, the higher degree of the smile is. Another measurement consists of seven-dimensional Emotion Confidence (EC), namely happiness, neutral, sadness, disgust, anger, fear, and surprise. The value of confidence of each emotion ranges from 0 to 100 and the sum of the 7 emotion confidences is 100. The higher confidence score of an emotion type is, the greater the dominance of the certain mood type achieves. This could help to determine the major emotion of a face expressed, which will be explained in the next section.

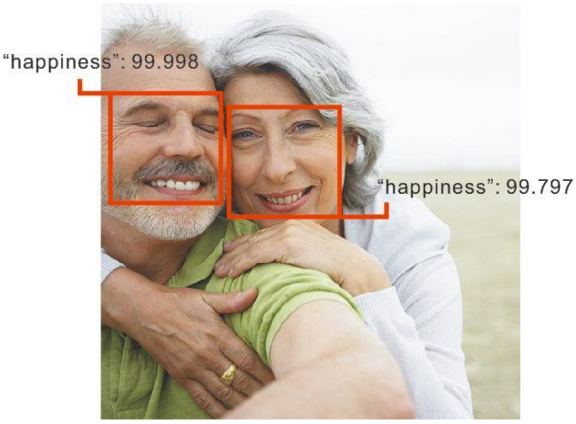

Figure 2 Example of happiness detected by Face++ (https://www.faceplusplus.com.cn/emotion-recognition/)

C. Emotion Indices

The next step in our research is to build assessment models for measuring human emotions in a specific region from a statistical view, especially to detect human happiness, as it is the most distinct mood. Two statistical indices are defined in our research. The first index is Average Smiling Index (ASI). We computed the average SF value with a certain number of faces.

For a given geographical area A, during the period t, the AHI is:

$$ASI_{At} = \frac{1}{n}\sum_{i=1}^{n} SF_{value}(i) \quad (1)$$

The equation calculates the average SF value of all faces and could show the degree of smiling. ASI illustrates the degree of happiness of people in the experiment area.

The other is Happiness Index (HI). Since the sum of the 7-dimensional emotions is 100, a face is judged as happy if the EC of the happiness is larger than 50, which means the face expresses happiness most. Thus, for a specific region A, a measure of the happiness over a period t is using the count of happy faces detected. However, considering that different regions have different count of faces, simply using count of happy faces is not suitable since it may cause data bias. For instance, the final result may be dominated by results of regions with a lot of faces. Therefore, in order to improve the accuracy of our result, we use the ratio of happy faces to the total faces.

$$HI_{At} = \frac{S_{happy}}{S_{sum}} \quad (2)$$

where S_{happy} is the count of faces with happiness of EC larger than 50, S_{sum} is the count of all faces. HI shows the proportion of smiling people in a certain region. Using the HI can also help us make comparison to the datasets with different size.

D. Robust Analysis

In order to test whether our facial-expression based emotion approaches are reliable, and to ensure the results are stable and can reflect the real emotional status that human expressed, we used bootstrapping strategy for robust analysis. Bootstrapping, a resampling approach, is commonly employed to approximate the distribution of test samples [36].

To explore whether our model is sensitive to the count of the faces, we used the following dataset D and D_i. D is constructed by random sampling 1% of faces from the whole face dataset. We thus obtained a dataset with about 130,000 faces. Then, a series of subsets of D are created, that is D_i. For each D_i, i photos are selected randomly by sampling, where $i = 1000, 2000, \dots, 20000$. Thus, there are 20 subsets of D and the bootstrapping strategy is adopted for each dataset with the following process.

a) Perform i times random sampling from D_i to form i new datasets with the same size of the origin dataset while with some elements repeated

b) Calculate the ASI and HI of each dataset respectively. And sort the results of these i ASI and HI.

c) Discard the lowest 2.5% and the highest 2.5% results, retaining the 95% confidence interval for ASI and HI of each dataset.

In this robust analysis, dataset D could represent the whole face dataset which is based on YFCC100 dataset and affective computing. While each D_i could represent any subset selected in our research. We aim at exploring how many faces are adequate in our experiment to get stable result. The confidence interval's size illustrates the sensitivity of the result of the emotion model to the count of data. A small confidence interval could show the result is stable.

E. Descriptive Statistics of Faces' Demography

Besides the emotion conditions recognized by the vision platform according to the facial expressions, some other features of faces can also be extracted. In fact, gender, ethnicity, and age could be computed thanks to the advanced computer vision algorithms [37]–[39]. Face++ platform also provides API which gives us the opportunity to take them into consideration in our research. We recorded them as well for further analysis.

Previous studies referred that there are systematic differences between East Asians and Westerns, since East Asians are more sensitive to contextual information, while Westerns tend to organize environment more analytic [40]. East Asians have smaller ratio size of faces than Westerns on Facebook [41]. Compared to Western culture, people from East smile less [42]. Hence, learning about the relationship between emotion and ethnicity can provide valuable views for cross-cultural research. Three groups of ethnicities could be divided clearly by Face++, that is Asian, White and Black. Then, we computed the emotion conditions of each ethnicity.

Prior researches examined the difference of emotion between men and women. Francine suggests that smile can reflect individual's status and man smile less than female [43]. Kring et al. had the similar result that women are more emotionally expressive than men [44]. Thus, we calculated the two indices of emotion for each gender.

In addition, age is considered in our research to find out in what age people are in better emotion status. Previous studies once used given names to refer ages since they are driven by social and cultural influences, which vary across space and time [45]. However, different regions and epochs may have the same given names of each individual which means it may have some bias. Facial expression-based age detection provides a new perspective. While compared with emotion, ethnicity and gender recognition, age classification is not accurate as well since people in the same age may have total different facial features. In order to improve the accuracy, we allocate faces into five groups according to the structural characteristics of the population all over the world and the standards of population division worldwide: (1) Child: 0-6 years; (2) Teenager: 7-17 years; (3) Youth:18-44 years; (4) Middle-aged:41-65 years; (5) Old: Larger than 65 years [46].

III. Result

A. Worldwide Faces

Totally, the count of faces recognized by Face++ platform is 13,478,816, with 8,685,681 photos detected in our research. Figure 3 visualizes the spatial distribution of these photos. Each face is symbolized as a yellow dot. A region with more dots represents a larger density of faces. Figure 4 shows the happiness condition based on SI in the worldwide, where a red point represents a face judged as smiling and a blue point vice versa.

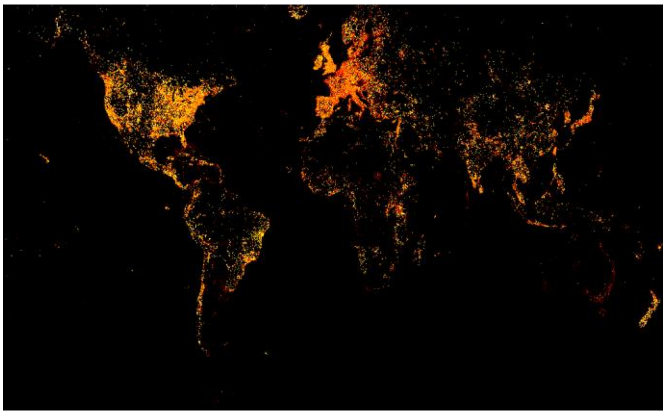

Figure 3 The worldwide geography of the 8.7 million photos. Each point represents a face located.

It can be referred directly from the map in Figure 3 that North America and Western Europe have more photos. New Zealand, Japan, and Korea also have a lot of photos.

From Figure 4, it can be shown that the majority of faces in North America are happy while fewer faces are smiling in Europe. And we calculated emotions in each country in the latter sessions.

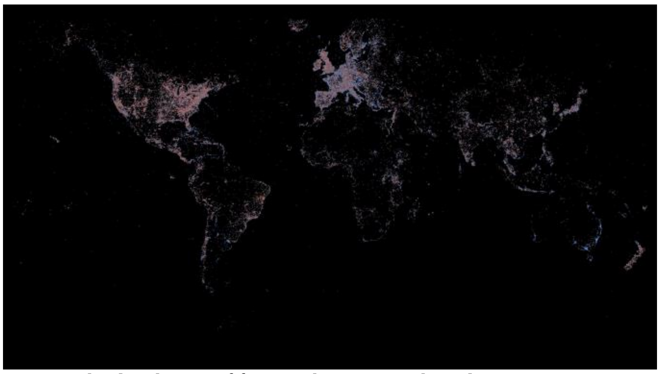

Figure 4 The distribution of faces with emotion. The red point represents the smiling face while the blue point shows a face not smiling.

B. Bootstrapping Strategy Results

Figure 3 and Figure 4 both show that Africa, Amazon Rain Forest, Siberia and some other unmanned areas have fewer photos. In order to ensure that our experiment has adequate data and could achieve a stable result, we used bootstrapping strategy. Figure 5 shows the result of ASI from 1000 faces to 20,000 faces and Figure 6 shows HI. In both two figures, the confidence interval is fit in well with the power law function fitting curve (R square is 0.998 and 0.999). It can be shown that when the dataset contains about 8000 faces, the interval of ASI would be less than 1.5, and the interval of HI would be less than 0.02. And if there are more than about 15,000 faces, the interval of ASI could be reduced less than 1 and the HI less than 0.015, which all show great stability.

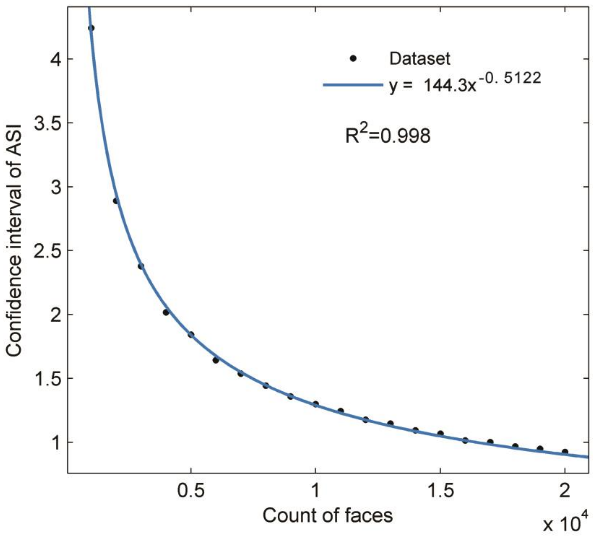

Figure 5 Bootstrapping strategy result of ASI (Average Smile Index)

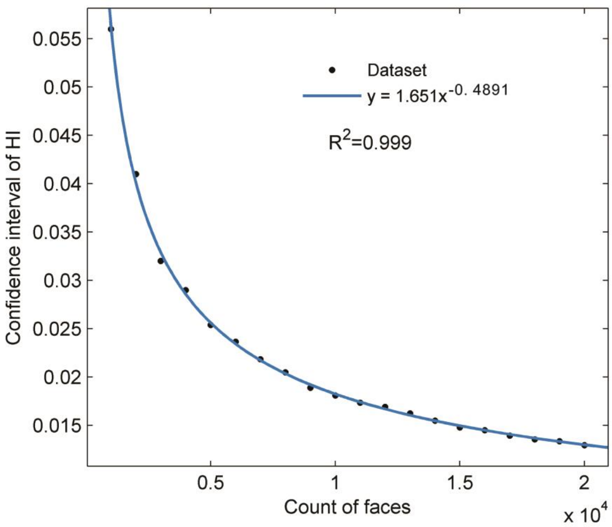

Figure 6 Bootstrapping strategy result of HI (Happiness Index)

C. Ethnicity

Our results from Figure 7 are in accordance with previous researches mentioned before that Asian do exhibit lower ASI and HI compared with White and Black. White have higher ASI while having lower HI than Black. Black have a higher ratio to be shot in a picture with a moderate smile, while Whites smile less, but smile bigger. We can conclude that emotional expression varies among different ethnic groups in the pattern showing in Figure 7.

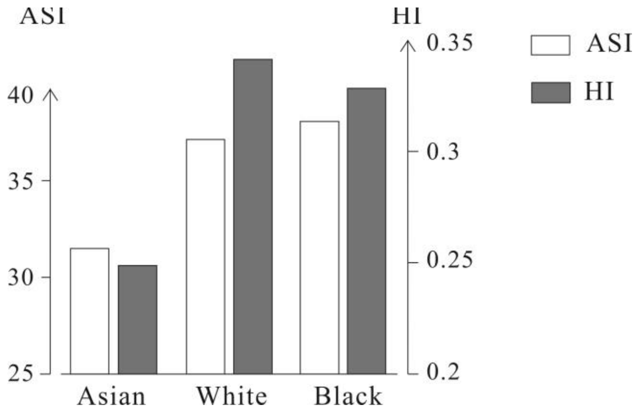

Figure 7 ASI and SI of ethnicity

D. Gender

Result in Figure 8 shows that based on our data, women's ASI and HI are both higher than men. This is an intuitive result, and also in accordance with previous studies. Thus, we can conclude that women express more happiness on their faces than men.

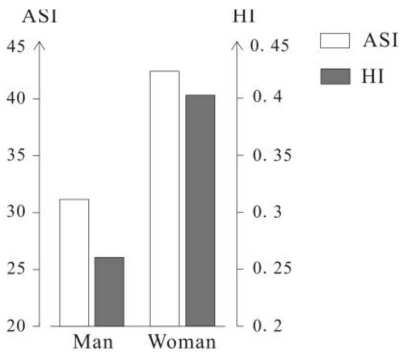

Figure 8 ASI and HI of gender

E. Age

Considering the result of ASI, with the age grows, ASI increases at first, and reaches the peak when people are middle-aged. After that, the ASI decreases but still higher than others. HI has the similar trend from teenagers to old people while the child has a higher HI. Results show that people in the middle-aged are happiest among all age groups.

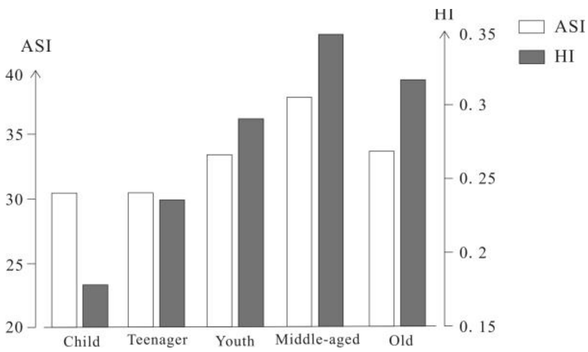

Figure 9 AHI and SI of age

F. Country

As once mentioned, we attempted to explore a global scale emotion distribution and YFCC100 dataset provide the chance to achieve our goal. According to the coordinates recorded in photo files, each face can be located to a country. Considering that different countries have no equal count of photos and some countries only have few faces detected, only countries with adequate photos should be selected in our experiment. After discarding countries with less than 100,000 photos, only 18 countries remained. We calculated emotion in each country and created a ranking list illustrated in Figure 10 as our result.

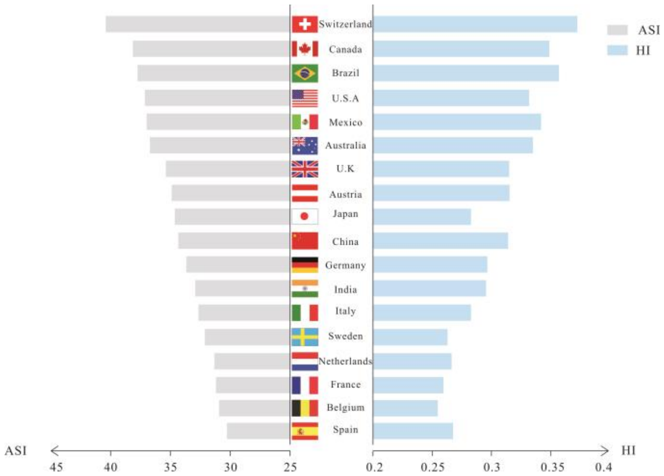

Figure 10 ASI and HI of 18 countries

G. Temporal Analysis

Time provides another dimension since the taken time of photos are recorded, therefore, we could trace and analyze the trend of emotion changes. Here we exploited AHI and SI tendency of every country which has enough photos along with year from 2004 to 2014. Figure 11 and Figure 12 show the ASI and HI change tendency of some countries selected. For each country, ASI and HI curves show the similar tendency. It can be shown that the happiness of people is falling down from a global perspective. Brazil, in particular, has the largest fluctuation of emotion. We explored some events happened during this period and would like to learn about whether there is some relationship between events and emotion expressed. An important discovery is that in 2008, when the global financial crisis erupted, ASI and HI in almost all countries decreased. Intuitively, economic conditions may influence human emotions, which is similar to previous studies [33]. In addition, 2006 World Cup was held in Germany and Italy won the final champion. From the results, it can be shown that people in these two countries were happier than the average in that year. The result might be explained by these large scale sports activities.

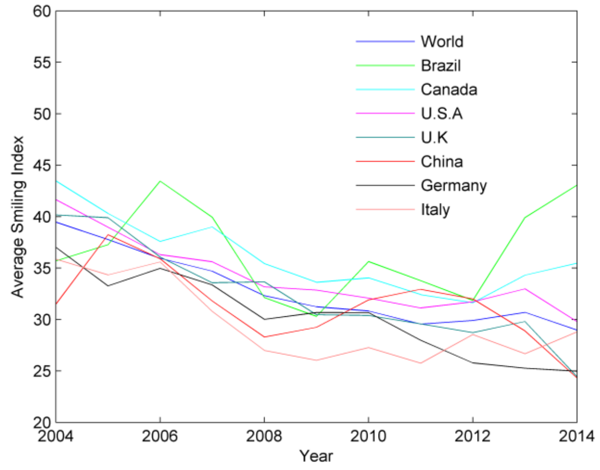

Figure 11 ASI change tendency through years of countries

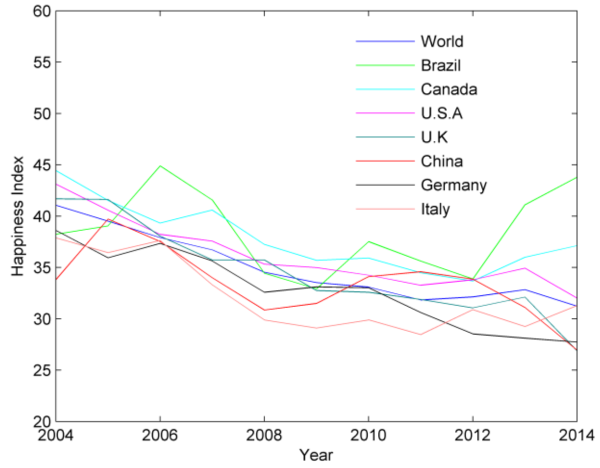

Figure 12 HI change tendency through years of countries

IV. CONCLUSION AND DISCUSSION

In this paper, a novel approach for measuring and qualifying human emotions are proposed. We explored how publicly posted pictures of human faces can reveal spatial and temporal trends in happiness, and serve as an indicator of mood. Results of emotions from a global scale are compared to demographic attributes with spatio-temporal analysis and achieve great stability.

According to our model, we concluded that White and Black are happier than Asian; women show much happier than men; and the middle-aged are the happiest people among all age groups; people in Switzerland and countries in North America present more happiness than people in Europe and East Asian, which means people in different regions represent different degree of happiness, and the difference could be detected and calculated. Our results are in agreement with conclusions of previous studies, which means the model proposed is feasible. What needs to be mentioned is that our methodology is not aimed at contrasting previous-studies and methods and to argue that our approach is better. We focus more on assessing and analyzing emotions from a new dimension and perspective with image dataset.

Also, some limitations about our image-based emotion extraction process and bias in our study should be addressed in our future work. Deeper relationships between facial expressions and real emotions still need further analysis from psychology and sociology aspects, to make sure to what extent emotion could be expressed by facial expressions. Plus, data bias still exists as the user group of Flickr is not universal.

Our future plan is to narrow down into smaller scales. This paper provides a large scaling experiment and attempts to make out contribution to anthropology. However, conclusions that can be established on a global scale may not be the same from a regional and local scale because of the existing of scale effect in geography. And a smaller scaled research may help to explain the result with simpler parameters. A bright direction is to exploit the spatio-temporal distribution and change of the human emotion from a more elaborate scale.

Another possible direction is to make data fusion with other data sources. And data bias can be reduced because different dataset could provide diverse insights from different dimensions of human emotion. Overall, we believe the techniques developed in this paper could be quite useful in affective computing and our approach is of potential research interest to the cross-cultural social science in the future.

ACKNOWLEDGMENT

The authors would like to thank Prof. Yu Liu in the Institute of Geographic Sciences and Natural Resources Research, Peking University, and Prof. Song Gao in the Department of Geography, University of Wisconsin Madison, for their impressive suggestions of our methodologies and insights. The authors also want to thank our team members Jialin Wang and Wenyuan Kong, who give us valuable suggestions and did data cleaning for this research and paper. This work is supported by the Fund for National College Students Innovations Special Project of China (Grant No. 201710486045).

REFERENCES

[1] I. Perikos and I. Hatzilygeroudis, “Recognizing emotions in text using ensemble of classifiers,” *Eng. Appl. Artif. Intell.*, vol. 51, pp. 191–201, 2016.

[2] S. A. Golder and M. W. Macy, “Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures,” *Science (80-.).*, vol. 333, no. 6051, pp. 1878–1881, Sep. 2011.

[3] E. Diener, M. Diener, and C. Diener, “Factors Predicting the Subjective Weil-Being of Nations,” *J. Pers. Soc. Psychol.*, vol. 69, no. 5, pp. 851–864, 1995.

[4] D. Quercia, “Don’t Worry, Be Happy: The Geography of Happiness on Facebook,” *ACM WebSci’13*, pp. 1–10, 2013.

[5] M. E. Larsen, T. W. Boonstra, P. J. Batterham, B. O’Dea, C. Paris, and H. Christensen, “We Feel: Mapping Emotion on Twitter,” *IEEE J. Biomed. Heal. Informatics*, vol. 19, no. 4, pp. 1246–1252, 2015.

[6] D. Quercia, J. Ellis, L. Capra, and J. Crowcroft, “Tracking ‘gross community happiness’ from tweets,” *Proc. ACM 2012 Conf. Comput. Support. Coop. Work - CSCW ’12*, p. 965, 2012.

[7] M. F. Goodchild, “Citizens as sensors: The world of volunteered geography,” *GeoJournal*, vol. 69, no. 4. pp. 211–221, 2007.

[8] M. Alivand and H. H. Hochmair, “Spatiotemporal analysis of photo contribution patterns to Panoramio and Flickr,” *Cartogr. Geogr. Inf. Sci.*, vol. 44, no. 2, pp. 170–184, 2017.

[9] Y. Liu *et al.*, “Social Sensing: A New Approach to Understanding Our Socioeconomic Environments,” *Ann. Assoc. Am. Geogr.*, vol. 105, no. 3, pp. 512–530, 2015.

[10] A. A. A. Esmin, R. L. D. O. Jr., and S. Matwin, “Hierarchical Classification Approach to Emotion Recognition in Twitter,” in *2012 11th International Conference on Machine Learning and Applications*, 2012, pp. 381–385.

[11] J. Bollen, H. Mao, and A. Pepe, “Modeling Public Mood and Emotion : Twitter Sentiment and Socio-Economic Phenomena,” in *Proceedings of the Fifth International AAAI Conference on Weblogs and Social Media*, 2011, pp. 450–453.

[12] P. S. Dodds, K. D. Harris, I. M. Kloumann, C. A. Bliss, and C. M. Danforth, “Temporal patterns of happiness and information in a global social network: Hedonometrics and Twitter,” *PLoS One*, vol. 6, no. 12, 2011.

[13] L. Mitchell, M. R. Frank, K. D. Harris, P. S. Dodds, and C. M. Danforth, “The Geography of Happiness: Connecting Twitter Sentiment and Expression, Demographics, and Objective Characteristics of Place,” *PLoS One*, vol. 8, no. 5, 2013.

[14] A. Bandhakavi, N. Wiratunga, D. Padmanabhan, and S. Massie, “Lexicon based feature extraction for emotion text classification,” *Pattern Recognit. Lett.*, vol. 93, pp. 133–142, 2017.

[15] A. D. I. Kramer, “An unobtrusive behavioral model of ‘gross national happiness,’” in *Proceedings of the 28th international conference on Human factors in computing systems - CHI ’10*, 2010, p. 287.

[16] L. Allisio, V. Mussa, C. Bosco, V. Patti, and G. Ruffo, “Felicitt??: Visualizing and estimating happiness in Italian cities from geotagged Tweets,” in *CEUR Workshop Proceedings*, 2013, vol. 1096, pp. 95–106.

[17] W. Wang and Q. He, “A survey on emotional semantic image retrieval,” in *Proceedings - International Conference on Image Processing, ICIP*, 2008, pp. 117–120.

[18] D. Borth, R. Ji, T. Chen, T. Breuel, and S.-F. Chang, “Large-scale visual sentiment ontology and detectors using adjective noun pairs,” in *Proceedings of the 21st ACM international conference on Multimedia - MM ’13*, 2013, vol. 28, no. 5, pp. 223–232.

[19] D. Joshi *et al.*, “Aesthetics and emotions in images,” *IEEE Signal Process. Mag.*, vol. 28, no. 5, pp. 94–115, 2011.

[20] D. Keltner, “Ekman, emotional expression, and the art of empirical epiphany,” *J. Res. Pers.*, vol. 38, no. 1, pp. 37–44, 2004.

[21] R. W. Levenson, P. Ekman, and W. V. Friesen, “Voluntary Facial Action Generates Emotion-Specific Autonomic Nervous System Activity,” *Psychophysiology*, vol. 27, no. 4, pp. 363–384, 1990.

[22] R. Adolphs, "Recognizing emotion from facial expressions: psychological and neurological mechanisms.," *Behavioral and cognitive neuroscience reviews*, vol. 1, no. 1. pp. 21–62, 2002.

[23] J. P. Seder and S. Oishi, "Intensity of Smiling in Facebook Photos Predicts Future Life Satisfaction," *Soc. Psychol. Personal. Sci.*, vol. 3, no. 4, pp. 407–413, 2012.

[24] P. Ekman, "An Argument for Basic Emotions," *Cogn. Emot.*, vol. 6, no. 3–4, pp. 169–200, 1992.

[25] H. A. Elfenbein and N. Ambady, "On the universality and cultural specificity of emotion recognition: A meta-analysis," *Psychological Bulletin*, vol. 128, no. 2. pp. 203–235, 2002.

[26] J. Freese, S. Meland, and W. Irwin, "Expressions of positive emotion in photographs, personality, and later-life marital and health outcomes," *J. Res. Pers.*, vol. 41, no. 2, pp. 488–497, 2007.

[27] L. A. Harker and D. Keltner, "Expressions of positive emotion in women's college yearbook pictures and their relationship to personality and life outcomes across adulthood," *J. Pers. Soc. Psychol.*, vol. 80, no. 1, pp. 112–124, 2001.

[28] P. Ekman and W. V. Friesen, *Facial Action Coding System: A Technique for the Measurement of Facial Movement*. 1978.

[29] J. Whitehill, G. Littlewort, I. Fasel, M. Bartlett, and J. Movellan, "Toward practical smile detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 11, pp. 2106–2111, 2009.

[30] V. Coetzee, J. M. Greeff, L. Barrett, and S. P. Henzi, "Facial-based ethnic recognition: Insights from two closely related but ethnically distinct groups," *S. Afr. J. Sci.*, vol. 105, no. 11–12, pp. 464–466, 2009.

[31] P. Ekman *et al.*, "Universals and cultural differences in the judgments of facial expressions of emotion.," *J. Pers. Soc. Psychol.*, vol. 53, no. 4, pp. 712–717, 1987.

[32] S. Abdullah, E. L. Murnane, J. M. R. Costa, and T. Choudhury, "Collective Smile: Measuring Societal Happiness from Geolocated Images," *Proc. 18th ACM Conf. Comput. Support. Coop. Work Soc. Comput. - CSCW '15*, pp. 361–374, 2015.

[33] Y. O. Kang, J. N. Wang, Y. O. Wang, S. Angsuesser, and T. Fei, "Mapping the sensitivity of the public emotion to the movement of stock market value: A case study of Manhattan," in *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, 2017, vol. 42, no. 2W7, pp. 1213–1221.

[34] U. Hess, M. Beaupré, and N. Cheung, "Who to whom and why – cultural differences and similarities in the function of smiles Ursula," *Millicent Abel smile Forms, Funct. consequences*, no. February, pp. 388–396, 2001.

[35] B. Thomee *et al.*, "YFCC100M: The New Data in Multimedia Research," *Commun. ACM*, vol. 59, no. 2, pp. 64–73, 2016.

[36] B. Efron, "Bootstrap Methods: Another Look at the Jackknife," *Ann. Stat.*, vol. 7, no. 1, pp. 1–26, 1979.

[37] O. M. Parkhi, A. Vedaldi, and A. Zisserman, "Deep Face Recognition," in *Procedings of the British Machine Vision Conference 2015*, 2015, p. 41.1-41.12.

[38] K. Ramesha, K. B. Raja, K. R. Venugopal, and L. M. Patnaik, "Feature extraction based face recognition, gender and age classification," 2010.

[39] F. Schroff, D. Kalenichenko, and J. Philbin, "FaceNet: A Unified Embedding for Face Recognition and Clustering." pp. 815–823, 2015.

[40] T. Masuda, R. Gonzalez, L. Kwan, and R. E. Nisbett, "Culture and aesthetic preference: Comparing the attention to context of East Asians and Americans," *Personal. Soc. Psychol. Bull.*, vol. 34, no. 9, pp. 1260–1275, 2008.

[41] C. M. Huang and D. Park, "Cultural influences on Facebook photographs," *Int. J. Psychol.*, vol. 48, no. 3, pp. 334–343, 2013.

[42] S. Lambot, E. C. Slob, I. Den Van Bosch, B. Stockbroeckx, and M. Vanclooster, "Modeling of ground-penetrating radar for accurate characterization of subsurface electric properties," *IEEE Trans. Geosci. Remote Sens.*, vol. 42, no. 11, pp. 2555–2568, 2004.

[43] F. M. Deutsch, "Status, Sex, and Smiling: The Effect of Role on Smiling in Men and Women," *Personal. Soc. Psychol. Bull.*, vol. 16, no. 3, pp. 531–540, 1990.

[44] A. M. Kring and A. H. Gordon, "Sex differences in emotion: Expression, experience, and physiology.," *J. Pers. Soc. Psychol.*, vol. 74, no. 3, pp. 686–703, 1998.

[45] P. A. Longley and M. Adnan, "Geo-temporal Twitter demographics," *Int. J. Geogr. Inf. Sci.*, vol. 30, no. 2, pp. 369–389, 2016.

[46] P. D. United Nations, Department of Economic and Social Affairs, "World Population Prospects The 2017 Revision Key Findings and Advance Tables," *World Population Prospects The 2017*, 2017. [Online]. Available: https://esa.un.org/unpd/wpp/Publications/Files/WPP2017_KeyFindings.pdf.