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Event photo mining from Twitter using keyword bursts and image clustering

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ABSTRACT

Twitter is a unique microblogging service which enables people to post and read not only short messages but also photos from anywhere. Since microblogs are different from traditional blogs in terms of timeliness and on-the-spot-ness, they include much information on various events over the world. Especially, photos posted to microblogs are useful to understand what happens in the world visually and intuitively.

In this paper, we propose a system to discover events and related photos from the Twitter stream. We make use of "geo-photo tweets" which are tweets including both geotags and photos in order to mine various events visually and geographically. Some works on event mining which utilize geotagged tweets have been proposed so far. However, they used no images but only textual analysis of tweet message texts. In this work, we detect events using visual information as well as textual information.

In the experiments, we analyzed 17 million geo-photo tweets posted in the United States and 3 million geo-photo tweets posted in Japan with the proposed method, and evaluated the results. We show some examples of detected events and their photos such as "rainbow", "fireworks" "Tokyo firefly festival" and "Halloween".

1. Introduction

Twitter is a unique microblog, which is different from conventional social media in terms of its timeliness and on-the-spot-ness. Many Twitter's users send messages, which are commonly called "tweets", to Twitter on the spot with mobile phones or smart phones. Therefore, Twitter users can be regarded as distributed "social sensors" which report what currently happens over the world [1,2]. In addition, many of tweets contain not only text messages but also photos. Then, Twitter users can be regarded as distributed cameras as well. In general, photos can explain what currently happens much more intuitively than texts. By using such distributed image sensors effectively, we can understand what kind of events happen over the world at this moment visually and intuitively. Although Twitter has been extensively studied as a distributed sensor of real-world trends and events, most of them are based on text analysis, and their outputs are usually event keywords with their locations and times, which do not explain the detail of the detected events. As distributed camera sensors, Twitter has not been explored extensively yet. This is mainly because the amount of Tweet photo data is too huge to collect and process in general. If the number of photos is very large, their visual analysis including features extraction and clustering naturally becomes computationally expensive.

In this paper, we propose a system to discover events visually from the Twitter stream. To tackle a large quantity of Tweet Photos, we adopt a two-step method consisting of event keyword burst detection based on textual analysis as the first step and clustering-based photo selection based on visual analysis as the second step. First we detect "events" with only textual analysis in the similar way as the existing Twitter event detection methods. Then we extract visual features from only images related to the detected events and carry out visual clustering to select photos associated with the detected events. Since we restricted tweet photos for visual analysis to the photos related to the detected event, the required computation is not so heavy. Thus the proposed method can be applied in a real-time event photo detection system from the Twitter stream.

To do that, we pay attention to the tweets having both geotags and photos. We call such tweets as "geo-photo tweets". So far some works on event mining which utilize geotagged tweets have been proposed. However, they used no images but textual analysis and geotag analysis. On the other hand, in this work, we detect events using visual information as well as textual information and geolocation information. To the best of our knowledge, this is the first work on Twitter event mining employing both text analysis and image analysis.

In the experiments, we analyzed 17 million geo-photo tweets posted from the United States in 2012 and 3 million geo-photo

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tweets posted from Japan from February, 2011 to September, 2012 with the proposed method, and then we successfully detected various kinds of event photos such as festivals, sport games, large-scale natural phenomena and some seasonal events. In addition, we implemented a real-time event photo detection system as well, and detected event photos in the real-time way.

To summarize our contributions in this paper are as follows: (1) We propose novel event photo mining from the Twitter stream, the results of which are useful to understand what happens in the world visually and intuitively. (2) A two-step method consisting of keyword burst detection and image clustering is proposed. (3) We made two large-scale experiments on the Japan dataset with 3 million geo-photo tweets and the US dataset with 17 million geo-photo tweets to show the effectiveness of the proposed method for event photo mining from Twitter.

The rest of this paper is organized as follows: Section 2 introduces related work, and Section 3 describes the overview of the proposed method on Twitter event photo mining. Section 4 describes the detail of the proposed method. In Section 5, experimental results are presented, and finally in Section 6 we conclude this paper.

2. Related work

In the multimedia community, an "event" is used in various contexts. Some work defined it as an activity in which people participate and take pictures such as hiking, playing sports at park and wedding party [3], while in the TRECVID Multimedia Event Detection task it was defined as an abstract concept of "action" or complex actions, and includes more personal activities such as making a sandwich, repairing an appliance and marriage proposal [4]. As another work on activity events, abnormality detection from video/image streams has been studied before [5]. The objective is to detect abnormal events such as invasions and accidents from fixed camera video streams. Recently, as its variant, detecting interesting events has been proposed [6]. They proposed a computational model which integrates multiple cues to evaluate visual interestingness of image sequences. These works focused on "event classification/recognition/detection" which was a kind of image/video recognition.

On the other hand, in case of "event detection", an "event" tends to become more public and to gather many people, since a certain number of photos or tweets related to a certain event are needed to detect the corresponding event. The MediaEval Social Event Detection (SED) Task defined "events" strictly as public events the schedules of which were announced on the Web event database, *last.fm*, such as music events and sport events [7], while in some event detection works the definition of "events" was broader and they allowed more personal events such as wedding to be regarded as "events" [8,9]. In our work, in addition to scheduled social events such as sport games and festivals, we regards natural phenomena as "events" such as typhoon, heavy

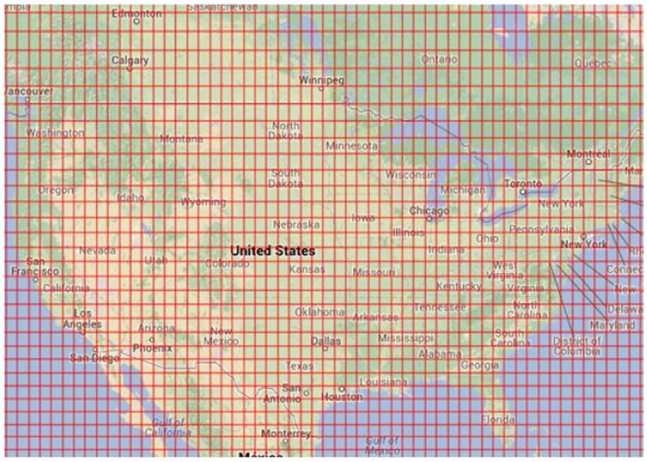

Fig. 1. The grids dividing the United States. Each of them is a unit area for event detection.

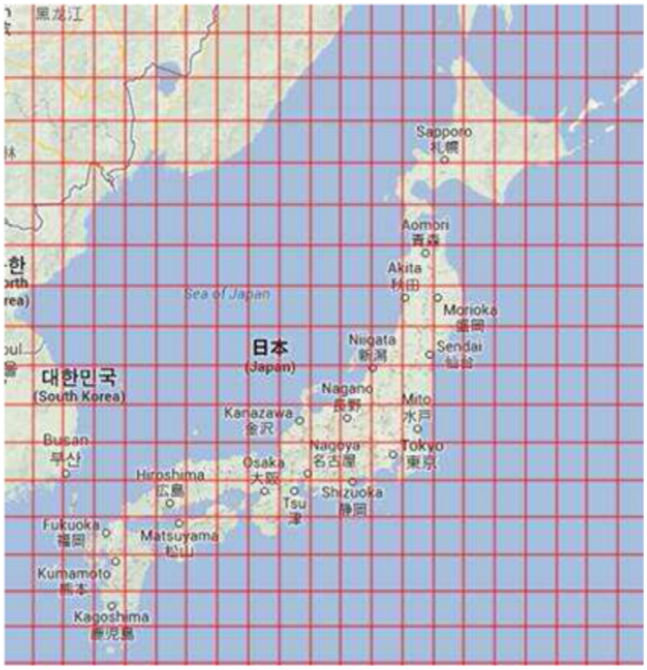

Fig. 2. The grids dividing the Japanese Islands.

Table 1
Part of the list of the extracted keywords from the Japan dataset.

Keyword	Date	Area	Weight	Score
snow	2011/2/11	34,35,135,136	1.96	135.5
earthquake	2011/3/11	35,36,139,140	1	55
fireworks	2011/8/6	34,35,135,136	1.96	149.2
festival	2011/8/6	34,35,135,136	1.96	68.7
Yodo-river	2011/8/6	34,35,135,136	1.96	72.6
dome	2011/8/10	43,44,141,142	3.96	51.5
rain	2011/8/19	35,36,139,140	1	60
typhoon	2011/9/21	35,36,139,140	1	62
Mt.Fuji	2011/9/24	35,36,138,139	3.35	67
Apple	2011/10/6	35,36,139,140	1	70
Ginza	2011/10/6	35,36,139,140	1	51
Suzuka	2011/10/9	34,35,136,137	3.94	78.8
eclipse	2011/12/10	34,35,135,136	1.96	84.4
Christmas	2011/12/24	35,36,136,137	2.9	55.2
New-Year's-Eve	2011/12/31	35,36,139,140	1	68
sunrise	2012/1/1	35,36,139,140	1	84
Meiji	2012/1/1	35,36,139,140	1	50
ski	2012/2/11	36,37,138,139	3.69	77.5
Marathon	2012/2/26	35,36,139,140	1	77
cherry-blossoms	2012/4/28	37,38,140,141	4.18	121.4
super moon	2012/5/5	35,36,139,140	1	96
firefly	2012/5/6	35,36,139,140	1	59
mother	2012/5/13	35,36,139,140	1	63
Tanabata	2012/7/7	34,35,135,136	1.96	56.9
Gion-Festival	2012/7/14	35,36,135,136	3.46	104
Tohoku-Denryoku	2012/7/14	37,38,139,140	4.4	79.2
peace	2012/8/6	34,35,132,133	4.08	77.5
Makuhari Messe	2012/8/11	35,36,140,141	3.18	168.9
Awa	2012/8/12	34,35,134,135	3.91	54.8
Daimonji	2012/8/16	35,36,135,136	3.46	83.2