

Visualization of Real-world Events with Geotagged Tweet Photos

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Background

- **Wide spread of mobile devices having GPS and cameras**

- **iPhone, Android**



- **Microblog service: **
- **Users can send images with geotagged messages on the spot.**



- **Twitter : new source of geotagged photos**

Twitter vs Flickr

- **flickr** : the most common geo-photo sources
 -  is different from **flickr** greatly.

	Flickr	Twitter
When	Offline upload	Instant (online) upload
Where	Upload at home	On the spot
How many	Many photos at once	One photo (or small num.)
What	Special personal event (e.g.travel)	Everyday life (e.g. foods), Something special photo
Purpose	Making online album	Posting a photo message

Geo-Twitter photos helps us to understand what and where happens intuitively.

Demo

- **World Seer: A Real-time Geo-Tweet Photo Mapping System [ICMR2012]**

- <http://mm.cs.uec.ac.jp/geotwphoto/>

Geotag tweet photos are very helpful to understand what and where happens intuitively over the world.

- ***Photos are posted on the spot instantly.***
- ***Photos are sometime reflected on the current “events”.***

Objective

Detect geo-photos related to the specific events from large number of geo-tweets with photos

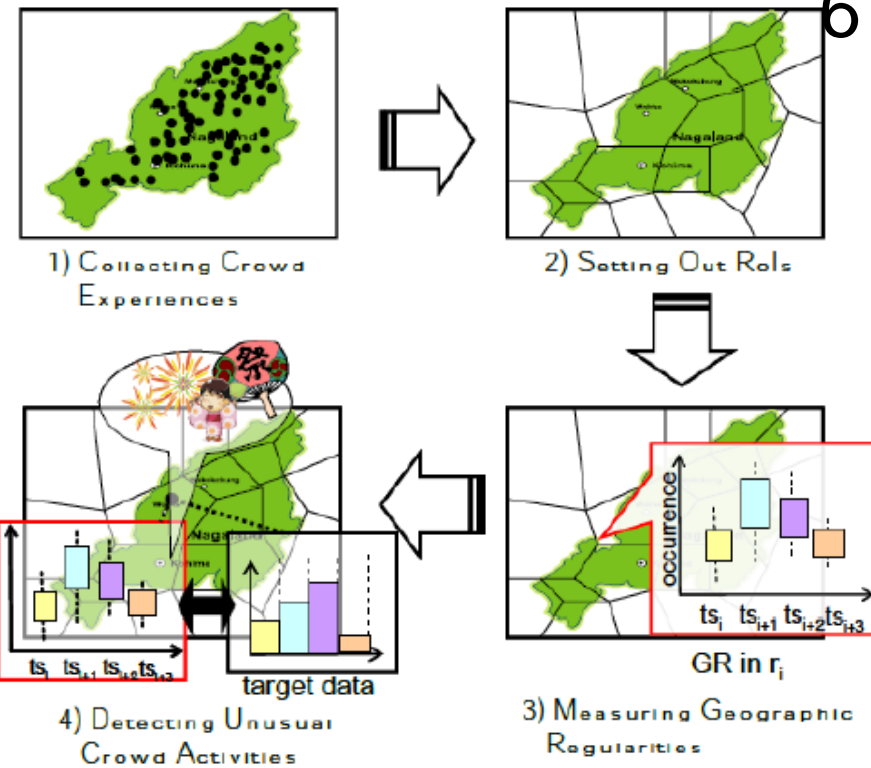
- **“Event” = related to many people in broad areas**
 - **Natural disaster**
 - **Bad weather**
 - **Festivals**
 - **Something unusual**
- **Representative photos for each place = correspond to representative event in the place**
 - **We can get to know what happens intuitively for each place.**



Users of geo-tweet photos = “social distributed-cameras”

Related Work : Event detection

- Many works on event detection
- Sakaki et al. [WWW2010]
 - Detect “earthquake” and “typhoon” and estimate their location
 - Twitter = “**Social sensor**”
- Lee et al. [SIGSPATIAL WS 2010]
 - Detect local events such as festival by considering #tweets, #users and user movements
 - Monitor the status of small local regions
 - If the status is normal or not (“burst of tweets”)



Existing works focused on analysis of geotagged texts.
They did not use photos at all.

Related work :

Selection of representative photos

- **VisualRank [Jing et al. PAMI2008]**
 - **Image ranking method based on PageRank**
 - **Image similarity is used instead of link structure.**

- **GeoVisual Rank [Kawakubo et al. WWW2010]**
 - **Extension of VisualRank for geotagged photos.**
 - **Consider location proximity as well as similarity**
 - **Bias vector is computed based on geotags**

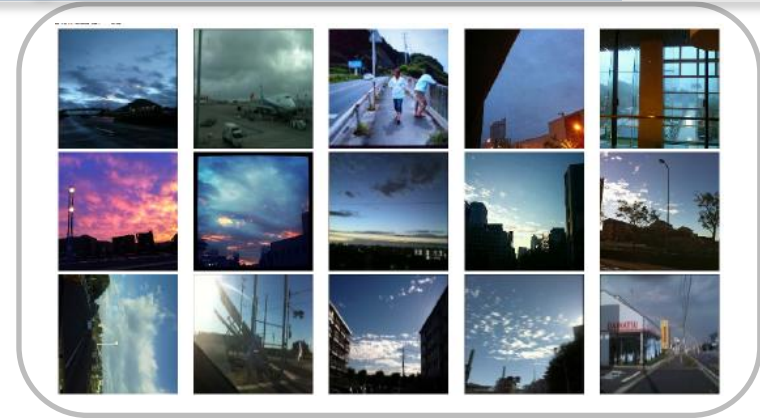


We use this method in this work.

Overview of the proposed system

Image cluster : looks similar

1. Image collection
2. Image feature extraction
 - Bag-of-Features with SURF
 - RGB color histogram
3. Clustering of locations
 - Mean-shift clustering
4. Selection of representative
 - GeoVisualRank
5. Showing similar images to the representative photos as "event photos"



Basically the method is similar to the work on landmark photo selection [Cradall et al WWW2009].

Difference of the photos = Difference of the situations

Data collection of geo-tweet photos




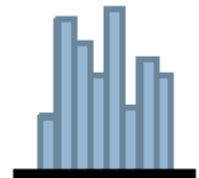
- **Via Twitter Streaming API** provided by 
- **[Data Collection System]**
- **Collecting geo-photo tweets from the Twitter stream continuously for 18 months**
- **Currently it has about 32,000,000 geo-photo tweets (200,000 photos / days)**
 - **[Yanai ICMR 2012] World Seer: A Real-time Geo-Tweet Photo Mapping System**
- **Photos are downloaded from twitter photo sites such as pic.twitter.com,**
 **twitpic** ,  **yfrog** and **Instagram** .

Image features

- **Before extracting features, we search the DB from images with given conditions related to locations, time periods, and keywords.**



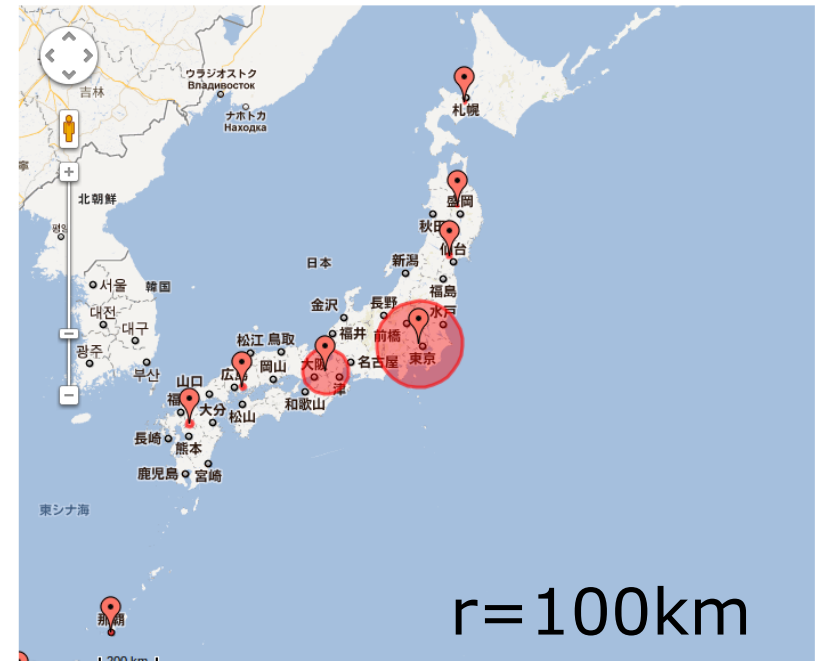
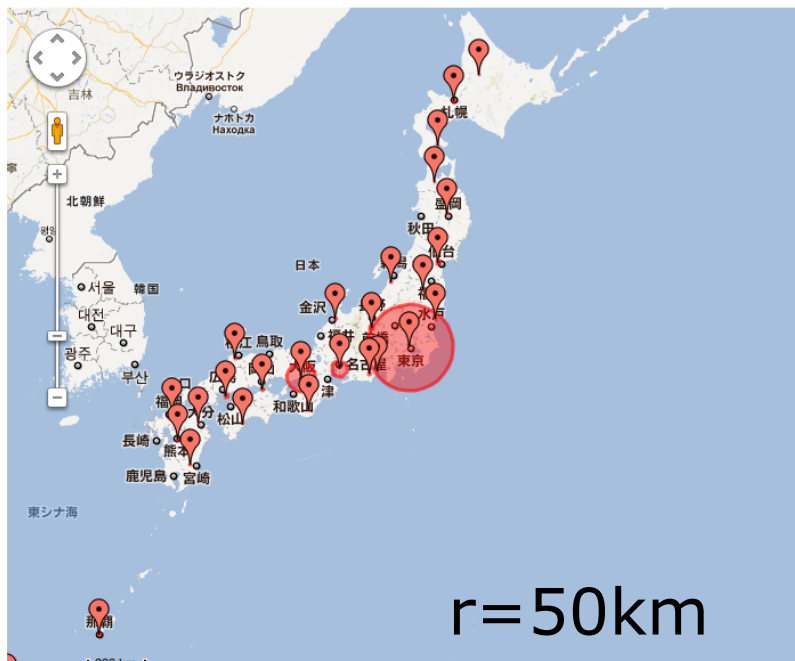
- **Bag-of-Features with SURF**
- **RGB color histogram**



We use them by fusing with equal weights.

Clustering of geotagged locations

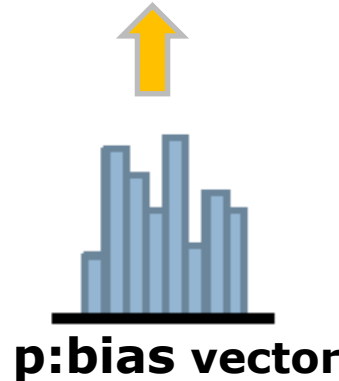
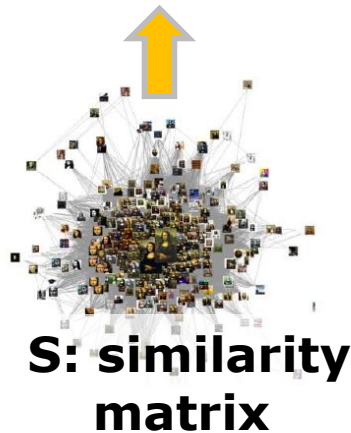
- Mean-Shift clustering
 - Clustering based on kernel density estimation
 - Given the radius of clusters instead of "k"



GeoVisualRank [Kawakubo et al. WWW2010]

- **Modification of VisualRank** (random walk on link-graph)

- $\mathbf{r} = \alpha \mathbf{S} \mathbf{r} + (1 - \alpha) \mathbf{p} \quad (0 \leq \alpha \leq 1)$



commonly $\alpha \geq 0.8$

- **Similarity: histogram intersection of BoF and color**
 - **Bias: based on the locations (proportional to the distance to the given reference point.)**

Temporal-extended GeoVisualRank

■ Modify GeoVisualRank so as to take into account time proximity

■ Bias vector: p^{geo}, p^{time}

- C^{geo} : imgs in given geo cluster

- C^{time} : imgs in given time cluster

- $n_{geo} = |C^{geo}|, n_{time} = |C^{time}|$

$$p^{geo}(i) = \begin{cases} 1/n_{geo} & (g_i \in C^{geo}) \\ 0 & (g_i \notin C^{geo}) \end{cases}$$

$$p^{time}(i) = \begin{cases} 1/n_{time} & (g_i \in C^{time}) \\ 0 & (g_i \notin C^{time}) \end{cases}$$

$$p = \beta p^{geo} + (1 - \beta) p^{time} \quad (\beta = 0.5)$$

■ Time cluster (6 hour/each -> 4clusters)

■ late-night 0am~6am

■ morning 7am~12pm

■ afternoon 12pm~6pm

■ night 6pm~0pm(midnight)

Experiments: case study

- **Case study for the three kinds of “events” with Japan**
 - **“Typhoon”**
 - **Given keyword: “typhoon”, term: Sept. 2011**
 - **Location: Japan**
 - **# hit geo-tweet photos : 616**
 - **“New year’s day”**
 - **Keywords: Japanese words related to “new year”**
 - (正月|おせち|日の出|はつひので|初詣|はつもうで)
 - **Term: Jan. 1st – 20th 2013**
 - **#hit geo-tweet photos : 1400**
 - **“Big earthquake” (March 11th 2011)**
 - **Keywords: none, location: Japan**
 - **Term: March 11th–12th 2011**
 - **#hit geo-tweet photos : 1080**

“Typhoon”

2011/09/01~
2011/09/30

■ Difference depending on locations

image cluster:33
緯度:-35.3411854,経度:-137.14069378

by pomepompeko
台風一過(^o^)/

at:Thu Sep 22 06:57:53
タグ:台風,過,する,今日,成る

@Nagoya

現在の注目時間:
0~6時

この位置の代表画像:

rank 1: 0.00291567	rank 2: 0.00287136
rank 3: 0.00286329	rank 4: 0.00284825
rank 5: 0.00281373	rank 6: 0.00279163
rank 7: 0.00273876	rank 8: 0.00273505
rank 9: 0.0027338	rank 10: 0.00271692

image cluster:22
緯度:40.283551,経度:140.556602

by katapon
台風過ぎて雨しとしと。【ホテルル...

at:Thu Sep 22 07:34:34 2011 JST
タグ:台風,一,する,雨,過,影響,,名

@Akita

現在の注目時間:
0~6時

この位置の代表画像:

rank 1: 0.0141137	rank 2: 0.0141083
rank 3: 0.0140226	rank 4: 0.0140114

“New year’s day”

2012/01/01~
2012/01/20

night

- Transition of event photos
 - “New year’s day” in Tokyo

現在の注目時間: [dropdown]

現在の注目時間: 19~23時

この位置の代表画像:

rank1: 0.00107 	rank2: 0.00106476
rank3: 0.00104993 	rank4: 0.00104941
rank5: 0.00104463 	rank6: 0.00104423
rank7: 0.00104071 	rank8: 0.00103892
rank9: 0.00103856 	rank10: 0.00103741

image cluster:10
緯度:35.3654648,経度:139.6322928

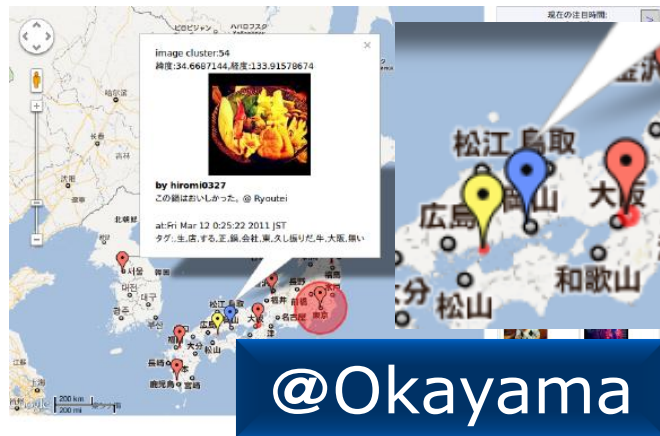
by kita86xbass
今年の正月は店の倉庫で寝ました

at:Sun Jan 08 22:00:56 2012 JST
タグ:初詣で,神社,正月,菖蒲,行く,する,靴,やる,実家,浅草,今

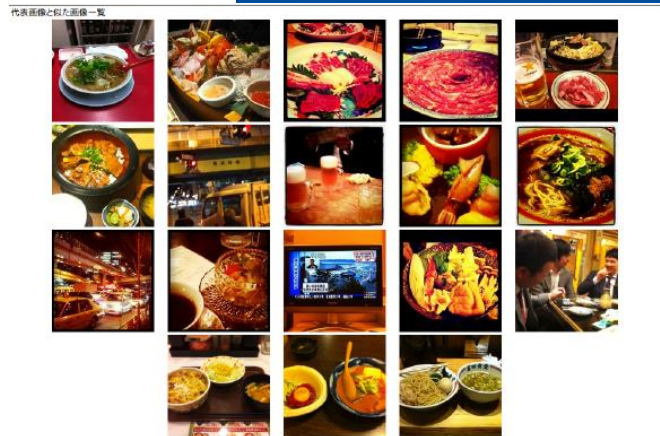
“Big earthquake”

2011/03/11~
2011/03/12

- Difference of the situation
 - Eastern part of Japan was unusual and much confused.



@Okayama



@Tokyo



Conclusions

- ***We proposed using geotagged tweet photos for event photo detection.***
 - ***“social distributed-cameras”***
- ***We used time-location VisualRank to detect event photos on the given location and the given time.***
- ***We can get to know about “events” intuitively .***
 - ***Different from text-based event detection.***

Future work

- **Real-time image-based event detection**
- **Use all the images over the world**
e.g. comparison of “new year’s event”
over the world
- **Use non-geotagged tweet photos as well**
 - **About 50~100 times as many photos as geo-photos are being posted.**

