Earthquakes: From Twitter Detection to EO Data Processing

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***Abstract*— The increase of social media use in recent years has shown potential also for the identification of specific trends in the data that could be used to locate earthquakes. In this work, we implemented a pipeline that uses Twitter data to identify locations of earthquakes and use the information to trigger EO data analysis. We tested the pipeline for almost a year over Japan, an area where earthquake events are frequent, as well as the use of social media in the population. Here, we show the results and discuss the potential development of such procedures. In the future, considering the rapid development and the increase of satellite constellations aimed at global coverage with short revisit times, algorithms of this kind could be used to prioritize satellite acquisitions for the detection of the areas most affected by earthquake damages.**

***Index Terms*— Earth observation (EO), earthquake, location identification, natural disaster management, social media.**

I. Introduction

EARTHQUAKES are major natural hazards, which cause every year severe damage and a threat to lives. The estimation of the earthquake's epicenter is usually achieved through the analysis of data recorded in real-time at several seismic stations. This information, which can be retrieved in almost real-time, is very important to define the area hit by potential damages and for planning a response in terms of disaster management. The accuracy on the epicenter's location depends mainly on the seismic data quality, as well as on the network density and geometry, which may differ across different areas of the world. Due to the recent diffusion of mobile devices (smartphones, tablets, etc.) and easier access to the internet, peaks in the rate of connections have been observed toward thematic websites and/or apps after an earthquake, as well as the use of social media. Recently, [1] reported that crowdsourced detection of seismic activity provides reliable locations of earthquakes, in many cases faster than established seismological protocols. Moreover, locations provided by "humans as sensors" have the advantage to deliver information on areas where earthquake risk is higher. Earth observation (EO) data have been increasingly used to identify and map permanent changes of the Earth's surface due to earthquakes and other geo-hazards. In this context, satellite SAR data can provide valuable information day and night and in any weather conditions. The recent developments toward higher spatial and temporal sampling allows obtaining quantitative measurements over areas hit by earthquakes with an unprecedented level of detail.

The presented work has derived as an outcome of the synergy between two completed EU Horizon 2020 projects in the "EO Big Data Shift" topic,[1] namely EOPEN,[2] which delivered an open, interoperable platform for unified access and analysis of EO data, and BETTER,[3] which provided an integrated big data intermediate service layer devoted to harnessing the potential of EO data. In this work, we implemented a pipeline that uses Twitter data to identify locations of earthquakes (based on EOPEN's social media crawlers) and use this information to trigger EO data analysis (based on BETTER's data pipelines), in particular, SAR data acquired by the ESA Copernicus Sentinel-1 [2].

The letter is organized as follows. In Section II, we discuss related publications about the analysis of Twitter and EO data, their combination, and their contribution to natural disaster management. In Section III, we present the two parts of the proposed pipeline: the collection and automatic geo-tagging of social media data and then the triggering of EO analysis. Section IV follows with a summary of the results of the proposed pipeline and discusses limitations and future work.

II. Related Work

Since the early years of the wide adoption of the Twitter social media platform, researchers have identified its value in

[1] https://cordis.europa.eu/program/id/H2020_EO-2-2017

[2] https://eopen-project.eu/

[3] https://www.ec-better.eu/

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the domain of natural disaster management, which includes the detection and damage estimation of earthquake incidents. In 2010, Sakaki *et al.* [3] suggested Twitter as a social sensor for real-time detection of events, such as earthquakes. The authors produced a probabilistic spatiotemporal model, which runs on tweets classified as relevant to a target event and uses Kalman and particle filters to discover the center and the trajectory of an earthquake's location. Earle *et al.* [4] managed to correlate the peaks in tweet-frequency time series, constructed from tweets containing the word "earthquake," with the origin times of widely felt events, but stated that no accurate location or magnitude can be assigned based solely on tweets. Other works assessed the potential use of geolocated data streaming from Twitter for earthquake detection and mapping the felt area [5] and investigated geocoded tweets to find temporal patterns of Twitter response as a function of distance from the earthquake epicenter [6]. More recently, Poblete *et al.* [7] proposed an online method for detecting unusual bursts in discrete-time signals extracted from Twitter, which only requires a one-off semi-supervised initialization and can be scaled to track multiple signals in a robust manner.

On the other hand, Mendoza *et al.* [8] applied named entity recognition (NER) on Twitter text and for each labeled location they used a fuzzy string matching procedure in order to map the location to its corresponding municipality. Then, they exploited these locations to provide spatial reports in the Mercalli scale, a qualitative measure to express the perceived intensity of an earthquake in terms of damages. Similar to our approach, Hernandez-Suarez *et al.* [9] combined language models based on NER techniques and a bidirectional long short-term memory (biLSTM) network to geoparse specific locations in tweets and used them to monitor natural disasters.

Another valuable source of information in disaster management is remote sensing and the use of satellite images. Guo *et al.* [10] analyzed and discussed technical methods and applications of optical technology for EO in monitoring geological disasters, such as barrier lake breaches, road damage, landslides, debris flows and numerous other secondary disasters. Moreover, Kaku *et al.* [11] presented how the analysis of satellite images assisted the planning of disaster countermeasures and the determination of the destruction extent over large areas that could not be viewed from the ground or by aircraft, with a focus on the 2011 Great East Japan Earthquake.

Regarding the combination of social media and EO data, Cervone *et al.* [12] described a two-step methodology where the real-time monitoring of Twitter data prioritizes the collection of commercial remote-sensing images, which are subsequently fused with social media images for assessing the damage of transportation infrastructure. Furthermore, Panteras and Cervone [13] suggested that the increased temporal resolution of crowdsourced data can partially compensate for the limitations of satellite data and thus presented a geostatistical analysis of combined satellite and Twitter data for the delineation of flood extent. More recently, social media data (Twitter text and images) have been fused with Sentinel-1 images on the snow depth estimation problem [14]. The use of relevant text and images that contain the concept "snow" has shown that it can improve the estimated snow depth, exploiting the massive ground observations from *in situ* social media posts.

TABLE I

NUMBER OF COLLECTED TWEETS FOR A ONE-YEAR-LONG PERIOD AND PERCENTAGES OF PROVIDED VERSUS EXTRACTED GEOINFORMATION

Collected	Geoinformation by Twitter	Geoinformation extracted
61,563	787 (1.28%)	39,695 (64.48%)

In contrast to the above methodologies, our work transfers the combination of satellite and social media data toward the detection of earthquake damages. In addition, our solution applies deep learning to extract the locations mentioned in the tweets text, instead of using Twitter's limited geoinformation, and uses openly available remote-sensing data, rather than commercial images.

III. PROPOSED PIPELINE

A. Collection and Geotagging of Social Media Data

Inspired by the various works that exploit social media data to detect earthquakes, the first part of the proposed pipeline focuses on the acquisition of relevant social media posts and their automatic geotagging in order to identify the locations of earthquakes. Among different social media platforms, Twitter has been selected, since it has been proven to be very popular in cases of natural disasters and it also provides a multitude of API endpoints for easily retrieving public tweets.

In detail, Twitter's *Standard Streaming API*[4] provides access to the public stream of Twitter data and tweets can be retrieved in real-time. In order to collect posts that are related to earthquakes in Japan, which is our use case scenario in this work, the Track request parameter has been used, i.e., a list of terms that determine what tweets will be delivered on the stream. Specifically, we have straightforwardly selected the terms "earthquake" and "Japan," thus only tweets whose text contained both words have been retrieved. By establishing and maintaining a continuous connection to the API for a whole year, we have managed to collect more than 60 thousand tweets from March 1, 2020, to February 28, 2021, that refer to earthquake incidents in Japan (see Table I).

Since the scope of this collection is to detect places of seismic activity, it is evident that the retrieved tweets have to be geotagged, i.e., to carry geographic information. Although Twitter can provide such information, we do not rely on it for two reasons: 1) since a policy change in 2019 [15], only a very low percentage of tweets are geotagged, which is also the case for our collection, as seen in Table I (just 1.2%) and 2) there is reason to suspect that the provided geoinformation does not correspond to the users' GPS coordinates anyway [15].

To this end, we perform an automatic geotagging methodology, presented and evaluated in [16], that transforms English tweets into georeferenced data by using their textual content to detect mentioned locations. After proper preprocessing, we employ NER techniques in the form of a pre-trained

[4]https://developer.twitter.com/en/docs/twitter-api/v1/tweets/filter-realtime/

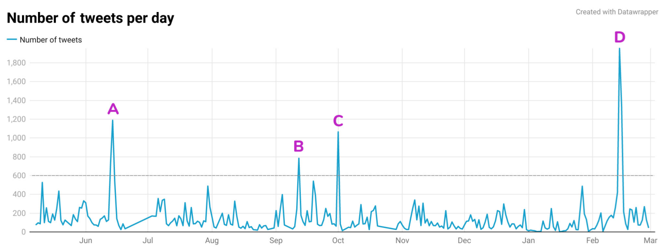

Fig. 1. Daily fluctuation of tweets from March 1, 2020, to February 28, 2021.

biLSTM-based model [17] to retrieve location-type mentions in the tweet's text. Single-word or multiword terms that are recognized as places are then associated with a geographical point (pair of coordinates) through a query to *OpenStreetMap (OSM) API*.[5] Applying this methodology to the collection, we have achieved to automatically geotag circa 65% of tweets, in compliance with Twitter's Developer Agreement and Policy,[6] ensuring that the extracted locations are solely associated with incidents and never with physical persons. The collected dataset (tweet IDs) and their derived geolocations have been publicly released to an online repository,[7] again in full compliance with the aforementioned policy.

The next step is to use this real-time collection of geotagged earthquake-related tweets to detect earthquake incidents. Based on the assumption that the occurrence of a real event will lead to higher activity on social media, we expect that the daily consumption of tweets will increase on a day when an earthquake happens. To prove this, we present the daily fluctuation of collected tweets during the examined year and attempt to associate peaks of the chart with specific earthquakes. In Fig. 1 a line chart shows the number of collected tweets per day and four main peaks are quite visible: 1) June 14, 2020; 2) September 12, 2020; 3) October 1, 2020; and 4) February 14, 2021. Although the dates of immense Twitter activity have been detected, they still have to be linked to locations. In order to visualize a spatial distribution of this activity, we have prepared heat maps that allow specific indication of which areas are most mentioned in the collected tweets (red color), based on the extracted coordinates. A separate heat map has been generated for each date (all focused to the bounding box of Japan, which is the use case of this work) and they can be seen in Fig. 2.

Viewing the most mentioned locations aids the identification of the exact earthquake that happened on each date and all four are given below. In order to validate that these results are connected to real incidents, relevant links from a reliable source, namely the *Global Earthquake Monitor of the Volcano Discovery* website,[8] are also provided as footnotes. It should be noted here that in most cases the activity on Twitter raises the day after the incident. In detail, the identified earthquakes are: 1) in Ryuku Islands on June 13, 2020[9]; 2) in the Near East Coast of Honshu on September 12, 2020[10]; 3) in the northeast of Sendai on September 30, 2020[11]; and 4) in Fukushima on February 13, 2021.[12]

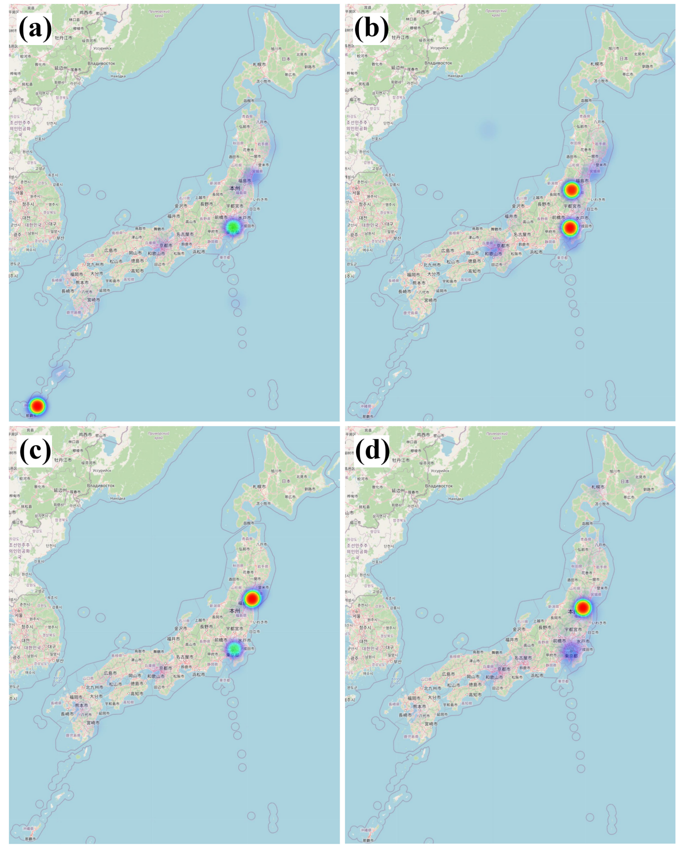

Fig. 2. Heat maps with most mentioned locations for each date of high Twitter activity: (a) June 14, 2020—Ryuku Islands, (b) September 12, 2020—Honshu and Tokyo, (c) October 1, 2020—Sendai Airport, and (d) February 14, 2021—Fukushima.

Since we have proven that earthquakes can be detected with Twitter data, the next step is to feed these data into the second part of the proposed pipeline, i.e., to trigger EO data analysis.

B. Triggering EO Analysis

As mentioned in Section I, the framework for triggering the EO data analysis was developed in the H2020 project BETTER, whose aim was to deliver a fully integrated big data intermediate service layer. This layer is dedicated to delivering customized solutions denominated "data pipelines" for large volume EO and non-EO datasets access, retrieval, processing, analysis, and visualization. The collaborative work environment (Ellip Solutions)[13] for assembling, testing, and validating these data pipelines is a cloud-based platform-as-a-service (PaaS), to access flexible and scalable data processing resources.

[5] https://wiki.openstreetmap.org/wiki/API

[6] https://developer.twitter.com/en/developer-terms/agreement-and-policy

[7] https://github.com/MKLab-ITI/geotagged-tweets-japan-eq

[8] https://www.volcanodiscovery.com/earthquake-monitor.html

[9] https://www.volcanodiscovery.com/earthquakes/2020/06/13/15h51/magnitude6-Japan-quake.html

[10] https://www.volcanodiscovery.com/earthquakes/5907629/2020-09-12/02h44/magnitude6-Japan.html

[11] https://www.volcanodiscovery.com/earthquakes/quake-info/5928378/mag4quake-Sep-30-2020-Near-East-Coast-of-Honshu-Japan.html

[12] https://www.volcanodiscovery.com/earthquakes/6097807/2021-02-13/14h07/magnitude7-Japan.html

[13] https://ellip.terradue.com

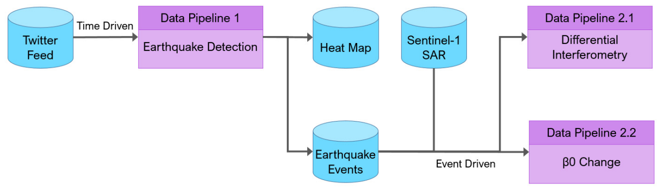

Fig. 3. Sequential data pipeline architecture.

The data pipeline used for this EO analysis is set such that the whole procedure is automatic from earthquake detection and selection of Sentinel-1 images to the production of EO products. Thus, the end-user can focus on the analysis and exploitation of said EO products. The overall flow and architecture can be divided into two sequential pipelines as seen in Fig. 3. The data pipeline 1 expands the work performed in [4] by using the data geotagged as described in Section III-A to detect earthquake events, associating the respective geolocalization and timestamps. This pipeline is time-driven, i.e., it is set to be triggered at predetermined time intervals. The data pipelines 2.1 and 2.2 focus on generating EO products for the events detected in the previous pipeline. These pipelines are considered event-driven due to the fact that they are only triggered when an earthquake incident is detected. It is worth noting that only events (groups of tweets), and not single tweets can trigger these pipelines, since millions of Twitter users post on a daily basis and this would lead to a new trigger every second and to multiple triggers for the same location.

In detail, the data pipeline 1 implements an event detector that is triggered by a high-frequency increase in the collected tweets that are geotagged within Japan (the country where a detected location belongs to is checked with OSM API). The "short-time-average through long-time-average trigger" (STA/LTA) algorithm is used. This algorithm continuously keeps track of the amplitude of tweets, where the STA is sensitive to current events, while the LTA provides information about the temporal amplitude, thus being able to filter out noise. Similar to [4], due to the specificity of the tweets studied, additional parameters are added to the ratio, required to account for low/null quantity of tweets. The characteristic function used during this study can be defined as

$$\mathrm{CF}(t) = \frac{\mathrm{STA}}{m\mathrm{LTA} + b} \tag{1}$$

where the STA and LTA windows chosen were 1 h and 10 days, respectively. Additionally, in order to make the algorithm more conservative, i.e., fewer false-positive detections, the values chosen for m and b are 2 and 1.

The algorithm considers a "detected event" when, during a continuous time window, the ratio value exceeds the preset value of 1. During this time window, all the tweet locations are registered. In Fig. 4, we can see that 3 out of the 4 earthquakes, initially considered in Section III-A, were indeed detected, while the earthquake on September 30, 2020, was not detected due to the fact that the STA/LTA ratio was approximately 0.9, indicating that the algorithm might be over-conservative with the current parameters. However, in Fig. 4, we can also see a detected event that was not clearly identified by the daily count of tweets and matches with a

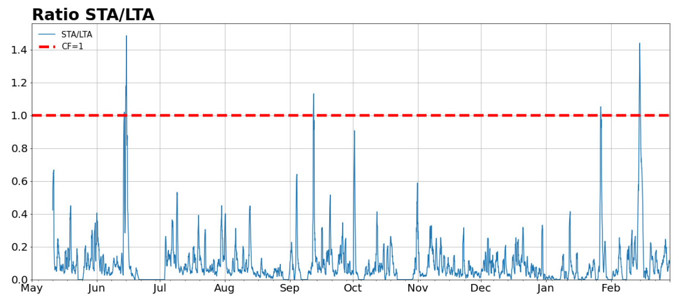

Fig. 4. STA/LTA ratio of collected tweets from May 1, 2020, to March 1, 2021.

magnitude 5.2 earthquake southeast of Chitose, Hokkaido, on January 27, 2021.[14]

The output of the data pipeline 1 is two different heat maps, which can be used to visually check the geo-distribution of tweets for each event similar to Fig. 2, and a CSV file containing the locations and timestamps of the detected events. This spatiotemporal information is then used to search for two Sentinel-1 SAR images that cover the location, one before and one after the event. Once the image pairs are found, the data pipelines 2.1 and 2.2 are automatically triggered.

The data pipeline 2.1 applies the DInSAR technique to generate interferograms from Sentinel-1 SLC pairs. The interferogram, a map of the difference in the phase between said images, largely reflects the surface deformation of the area illuminated by the radar during the period between the two acquisition dates [18]. With this technique, centimeter displacements can be measured; hence, it is one of the main EO approaches to monitor seismic deformation. This pipeline also computes the interferometric coherence (phase correlation, i.e., quality of the differential phase measurement) of the two SAR images, which is related to phase noise. It is important to assess the interferogram quality and can also be used to detect big changes in the surface morphology (loss of coherence) caused for example by landslides.

The data pipeline 2.2 computes the Beta Nought (β_0) radar brightness coefficient change from Sentinel-1 SLC pairs. Computed as natural logarithm of the ratio of β_0 (log-ratio) between the two acquisition dates, these changes can be used to detect landslides based on the assumption that a landslide episode alters the local land cover and some of its properties (roughness and/or the complex dielectric value) affecting the radar amplitude [19].

IV. Summary and Conclusion

The pipeline produced several differential interferograms and coherence maps for all Sentinel-1 pairs acquired timely across the earthquakes over the geographic regions identified. Considering the relatively large depths (>30 km) of the four earthquakes of this pilot test during the period of investigation, no permanent surface deformation or damages were detected in the EO results. Nevertheless, the pipeline provided automatically a full set of results over the areas of interest without any human intervention, allowing the end user to focus only

[14] https://www.volcanodiscovery.com/earthquakes/quake-info/6075056/mag5quake-Jan-27-2021-Hokkaido-Japan-Region.html

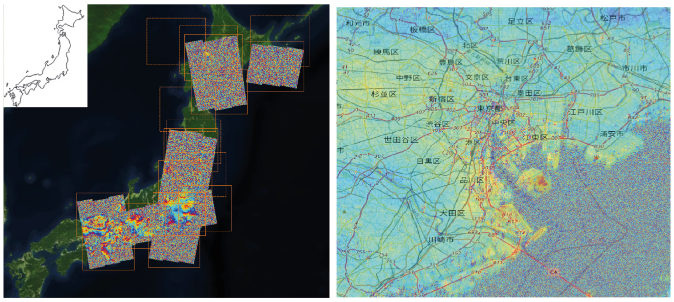

Fig. 5. Pipeline results obtained for the event occurred on February 14, 2021. (Left) Overview of the differential interferograms produced. No evidence of widespread co-seismic surface deformation is identified. (Right) Example of thematic map (surface deformation) generated by downloading a specific interferogram of interest covering the city of Tokyo.

on the exploitation of the results rather than on EO dataset identification, collection, processing, and interpretation. This is extremely useful in a scenario where a large area needs to be permanently monitored due to high earthquake risk.

Fig. 5 shows the visualization of the results (e.g., differential interferograms) that can be initially explored and evaluated online, as well as eventually downloaded for further analyses. One of the limitations noticed at this stage is that the pipeline has produced a very large number of results in areas that are also far from the epicenter's region. This is because after the initial identification of an event (trigger of the processing pipeline) tweets continue to flow for several days afterward and in broader regions. Another possible limitation is that high activity can relate to a past event (e.g., a disaster anniversary), while falsely detected locations can lead to false triggers. Thus, further tuning of the triggering procedure is needed to avoid an excess of information in areas not affected by the actual event. A suggested solution is to consider a multistep location and refinement of the area of interest, based initially on social data and then adapted by considering the seismic data, i.e., similar to what has been proposed by [1].

Other interesting research directions would be the development of a NER model for Japanese, so as to geotag tweets in the predominant language of the country, and the investigation of how the accuracy of crowdsourced information changes with regards to the proximity to the time that an earthquake incident happens, e.g., during the seismic activity, some minutes/hours after the event, etc., also taking into consideration the possibility of fake news being spread on social media.

In conclusion, our results show that the information provided by "humans as sensors," through social media, such as Twitter, can be used to trigger specific EO processing. In the future, considering the rapid development and the increase of satellite constellations aimed at global coverage with short revisit times, algorithms of this kind could be used to prioritize satellite acquisitions over the areas most affected by a natural disaster, as well as to produce systematically and rapidly thematic maps of help for disaster risk management.

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