INVITED PAPER

Spatial Technology and Social Media in Remote Sensing: A Survey

This paper provides an overview on the integration of social media content with remote-sensing-based spatial technologies.

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ABSTRACT | The rapid development of social media data and the associated growth in volume, velocity, and variety has fostered the idea of using these data to guide traditional remote sensing image retrieval and information extraction tasks. Although important progress has been made in recent years in harvesting spatial and temporal data from social media, the exploitation of these data for decision making still needs further investigation, particularly in the context of its integration with remote sensing and geographic information systems. In this paper, we first discuss the relation between localization techniques and spatial technologies, pointing out their similarities and differences. Then, we provide a discussion on location analysis of social media data, and the fusion of multiple data sources, with specific attention to the integration of social media content (including localization) with remote sensing-based spatial technologies. Next, we provide specific examples addressing the use of social media data to perform information extraction from large remote sensing data repositories. Although significant possibilities for the integration of localization and spatial technologies can be seen in the examples provided, our survey suggests that the convergence of remote sensing and social media data will continue to deeply transform these technologies.

KEYWORDS | Localization; remote sensing; social media; spatial technologies

I. INTRODUCTION

The significant development of social media has been complemented by the rise of spatial technologies leading to the development of new mapping techniques that allow users engage with online information services and with each other in an unprecedented way [1]. Fostered by the adoption of global positioning system (GPS)-enabled smartphones, users now exploit social media data in completely new ways. For example, the Instagram image sharing service allows users to attach their geographical coordinates to a photograph (positioning), allowing for the sharing of location information in social networks [2]. Similar services are provided by other image services like Flickr [3]. These "footprints" can be associated to Earth observation data coming from satellites and other sources of data coming from geographic information systems (GISs), opening new avenues for human interaction and establishing the basis for new geosocial environments [4]. In addition, developers of information technology systems such as web systems [5], social media [6], and sensing systems [7] can now include these footprints into user-based models and "location-aware" (monitoring) services. Specifically, these footprints (which are spatiotemporal in nature) provide new opportunities to explore complex matters such as human behavior dynamics and social life.

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Many studies have been presented addressing the aforementioned topics in the context of remote sensing [8], [9], data mining and machine learning [10], GIS [11], web search and information retrieval [5], or high- performance computing [12]. For example, if access to Facebook data is available [13], these data can be used to explore how social networks are related to geographical aspects [14]. Remote sensing satellite data have been combined with information coming from social media and spatial mapping services in order to monitor the impact of natural disasters [15]. New information systems have been developed by exploiting the information provided by location cues, including relevant examples such as earthquake monitoring using Twitter and Facebook data [16]. The term "big data" [17] is now commonly used to address data sets currently managed by remote sensing, social media, and GIS systems. This term is relevant in our context due to the massive amount of data that is currently being generated by GIS, remote sensing, and social media data repositories, which offer completely different sources of data.

In remote sensing applications, sources and instruments currently available for Earth observation [18] generate different types of airborne or satellite images with different resolutions (i.e., spatial resolution, spectral resolution, and temporal resolution) and collected from different kinds of instruments (e.g., multi/hyperspectral [19], synthetic aperture radar [20], etc.) This raises a demand in data analysis techniques, such as automatic classification [21], multitemporal processing [22], or data fusion [23], [24], which can greatly benefit from high-performance computing architectures [19], most notably cloud computing platforms [25].

In the context of social media, the information provided by social networks allows for a new understanding on the sharing of information from a global perspective [26]. Just as an example, Twitter generates about 500 million of tweets on a daily basis [27], and some of these tweets can be geolocalized using latitude–longitude information [28]. An exploration of the localization dimension of these tweets can lead to additional cues when interpreting remote sensing data.

A similar observation can be made for GIS systems, which can benefit from the information provided by social media in order to communicate and share knowledge [11]. At this point, it is worth mentioning that virtual communities for information exchange have become extremely popular in recent years. For instance, Google Maps already formed a community comprising millions of users. OpenStreetMaps, on the other hand, also has a very active community, although with fewer users [29].

The confluence of remote sensing technologies and GIS with (social) media, together with recent advances in services, is creating new perspectives toward the integration of these different data sources. However, merging social media data with other data is still a highly complex procedure fraught with problems [30]. This large amount of data [17] requires advanced data mining and processing techniques [10], [31], coupled with adequate high-performance computing infrastructure [25]. Although important progress has been made in recent years toward the collection and understanding of spatial and temporal data from social networks [32], the use of these data for efficient decision making still needs further research. Accomplishing this will require new methods, algorithms, systems and (particularly) big data processing frameworks, allowing us to analyze large amounts of data, which can include very high-resolution satellite imagery [33] and spatiotemporal information from social networks [34]. The new developments made in these directions are expected to introduce significant advances in upcoming years, together with the increased attention to spatial technologies, social media, and high-performance computing approaches [35], [36].

In this paper, we intend to provide a snapshot of the most recent advances and breakthroughs in the aforementioned areas, with particular focus on the combination of remote sensing data and information coming from social media, under a big data processing framework. The remainder of the paper is organized as follows. Section II discusses the relation between localization techniques and spatial technologies, pointing out their similarities and differences. Our motivation for including this section is to first set the terminology and fundamental concepts that will be developed later on in the paper. Section III provides a discussion on fusion of multiple data sources. We feel that this is a very important aspect, under which the convergence of (geolocalized) social media data can take place. Our discussion is focused on general schemes available in the literature, with specific attention to the integration of social media data (including localization) with remote-sensing-based spatial technologies. Section IV expands on this issue and provides specific examples addressing the use of social media data to perform information extraction from large remote sensing data repositories. The discussed examples are shown to fit under the general fusion frameworks described in Section III. These examples are categorized and described in terms of the data sources being used and other relevant parameters. Finally, Section IV concludes the paper with some remarks.

II. LOCALIZATION TECHNIQUES AND SPATIAL TECHNOLOGIES

In this section, we provide an overview of the relation between localization techniques and spatial technology, with the ultimate goal of pointing out their similarities and differences. The exponential growth in social media over the past decade has been complemented by the rise of localization as an important concept that allows users engage with online information services [37]. Geosocial tags provide a large amount of geolocalization information with the potential to support scientific research studies [38]. Previous difficulties related with the proprietary nature of localization data, the cost of acquiring new data through small-scale studies, or the difficulty of sharing such data are now overcome [39], and it is time to integrate these sources of information into other more consolidated technologies, such as spatial ones. In fact, spatial technologies already provide tools to incorporate and analyze large data sets in a meaningful manner. Examples of spatial technologies are GIS and remote sensing.

- GIS is a technology that is specifically intended for handling geographic data available in digital form. It has the ability to process large amounts of data; to develop models that perform data analysis, calibration, forecasting, and prediction; and to provide final results in different forms [40].
- Remote sensing involves the use of systems and algorithms to record information about surface of the Earth from a remote localization. A subsequent challenge is how to develop realistic spectral, spatial, and temporal models for extracting relevant information from these data. This task is normally related to a view of the image-forming process [41], where it is important to distinguish between the scene and the image. While the scene is real and exists on the surface of the Earth, the image is a collection of spatially arranged measurements that are used to represent the scene [42]. As a result, the goal of remote sensing models is normally to infer the characteristics of the scene from the image.

Big data and cloud computing technologies [43] are essential for exploiting the data generated in GIS and remote sensing applications. This is mainly because of the enormous data volumes generated, which need to be efficiently processed, managed, and stored. The further inclusion of social media data brings additional computational challenges.

III. FUSION OF MULTIPLE DATA SOURCES

In this section, we highlight the importance and techniques involved for combining multiple data sources, required in order to fully complement remote sensing and GIS data with information coming from social media. Our idea is to discuss a general framework under which the convergence of (geolocalized) social media data can take place. For this purpose, we first describe available techniques for location analysis and data mining. Then, we summarize some available strategies for fusing social media and remote sensing data, addressing specific challenges in this task. In the following section, we provide specific examples and representative case studies of some of the strategies discussed in this section.

A. Location Analysis for Social Media Data

Location is a critical source of information in order to relate social media data to remote sensing and geospatial context-aware applications. We give a short survey of location analysis techniques in two aspects: 1) location detection and distance analysis of social media users; and 2) location classification of social media content.

1) Detection of User Locations: Location estimation of users is important to extract relevant information from social media data for high-quality geospatial application integration. Location detection techniques can also facilitate distance-sensitive mining, for example, mining group activities of social media users within a geolocation or a distance radius. There are three location types that social media users can include: the access location of computer devices, the home location of a user where a user lives, and the visit location of a user. While multiple data sources can be leveraged to improve location estimation, the availability of such data sources varies based on application settings and may be affected by privacy constraints as many users choose not to reveal their location-oriented data. Techniques for user location detection can be categorized as IP/browser oriented, content driven, and network based.

The simplest way to identify the location of users which access and post social media is to leverage HTML5, which provides geolocation API support so that a user's browser can find its geolocation based on its IP address. Naturally privacy is a big concern when such a location is shared to any Internet application. In fact, the latest Chrome release does not support obtaining the user location through HTML5 geolocation API from pages delivered through nonsecure connections [44]. As a result, the geolocation information of users may not be collectable from browser data. It is possible to map an IP address into a city level. Several IP geolocation databases that map IP addresses to their geographical locations are available and used by many services and web sites, and these databases are not highly reliable [45]. Techniques are studied in [46] to improve the accuracy of IP geolocation mapping using the user log data.

When a user is associated with additional information such as tweets or friend circles, the accuracy of location detection can be greatly improved by content mining and network-based estimation. The algorithms proposed in [47] predict the home location of Twitter users hierarchically from tweet contents and tweeting behavior in addition to external location knowledge. Their prediction hierarchy includes city, time zone, state, or geographic regions. The research in [48] addresses location detection through social and spatial proximity by leveraging relationships expressed on the Facebook network. In this scheme, the user's location can be derived by the geography of his or her friends, and they show that their network-based detection accuracy can outperform the IP-based methods significantly. The online location inference method over social streams proposed in [49] exploits the spatiotemporal correlation, and continuously updates and improves inference results based on the newly arriving contents. The key idea is to infer the locations of users who simultaneously post about a local event.

User home location detection can be enhanced when distance information among users is derivable. The network-based location estimation [48] is further improved in [50] by integrating evidence of social tie strengths between pairs of users and their distance estimation. This scheme in [50] incorporates uncertainty across multiple location granularities and trains a tree classifier to estimate the distance between a pair of connected users.

The derivation of visit location of users needs to consider the impact of time. The PRED model in [51] further extracts periodic location patterns of social media users: how often an individual person visits a geographical region. Such information enhances location- and time-aware services based on human mobility patterns. The study in [52] develops a framework to extract points of interest (POIs) mentioned in social media content with temporal awareness and predict whether the users have visited or will soon visit such places. Their solution integrates data from Twitter and Foursquare with time-aware POI extraction.

2) Location Classification for Social Media Content: Classification that maps social media content to geolocations is desirable to identify geospatial interests expressed in such content. There are two types of location involved: what location is mentioned or focused on in a posted message and from where such a message is posted.

Geolocation prediction of twitter texts is studied in [53] and the authors have presented an integrated geolocation prediction framework and evaluated a range of feature selection methods that serve as an indication of locations. The machine learning methods for geolocation detection of text documents such as Wikipedia and Twitter data sets are studied in [54] and [55]. The work in [56] discusses a hierarchical discriminative classification method for text-based geotagging. The authors demonstrate the effectiveness of using logistic regression models to improve the accuracy by geolocation detection for Twitter, Wikipedia, and Flickr data sets.

The posting location of social media messages can often be different from author's home location since the same person can post messages from different locations at different times. The recent work in [57] studies the impact of time on the geolocation of social media content and predicts where a post was made.

Fine-grain level locations mentioned in social media content can be further clustered and the recent scheme proposed in [58] performs location recognition in tweets and also links them to well-defined location profiles in Foursquare using a beam-search-based algorithm.

For social media content which involves photo images, the classification method developed in [59] estimates locations of photos based on their visual, textual, and temporal features. The authors evaluate their techniques with a large collection of Flickr images based on text tags and geospatial data. The recent work in [60] develops an algorithm with adaptive localization that exploits picture-oriented social networks such as Instagram to detect urban events, exploiting physical proximity embedded in the social network data and temporal and location data in photos.

B. Integration of Social Media and Remote Sensing Data

The incorporation of social media information and remote sensing-based spatial technologies offers an important new perspective toward the joint exploitation of both kinds of data in synergistic fashion. This is what we refer to as integration, i.e., the combined exploitation of both sources of data in a common framework. For instance, relating publicly available social media information on certain locations with remote sensing data can lead to a more efficient disaster response [61]. After a disaster, response teams commonly use satellite imagery, but these images may not be always available in a timely manner. As a result, there has been a growing interest in using social media to complement the information available from satellite images. However, the specific technical challenges related to mining social media data often represent a hurdle for the achievement of such goal. Specifically, the inherently linked nature of social media data further complicates the task. Trust is also a concern, and challenges arise from a lack of computational understanding of distrust with social media data. Finally, information intended to deceive can spread though social media in the same way as valid information. This raises questions of how to detect different types of deception.

Due to the need for real-time information, previous research works have focused on the development of techniques able to integrate data coming from different sources [62]. Some studies have developed machine learning techniques to automatically analyze a large number of images, together with data coming from social media. For instance, Twitter data have been analyzed to complement satellite images [63]–[65] and identify additional flooded areas other than those found using satellite images [66], [67]. These studies demonstrate that relying on satellite data only may not be completely effective. In addition, there is a need to integrate satellite data with other sources of remote sensing data such as those coming from unmanned aerial vehicles or airplanes, and also with social media data.

In recent years, we have seen more efforts toward the integration of remote sensing and social media data [62]. However, such integration poses some new processing challenges. For instance, it results in large volumes of data, and there is currently a lack of frameworks which are specifically intended for the synergistic exploitation of remote sensing and social media data. Cloud computing platforms have been used to provide the necessary computing resources [21], and this has been particularly useful in different application domains [68]. Up to date, remote sensing data (e.g., optical, radar, and LiDAR) are now readily available, but social media data provide an additional data layer source that can be particularly helpful in applications such as urban data analysis [68].

The processing of such massive amount of integrated social media and remote sensing data (collected from various sources) creates the need to synthesize the relevant aspects of these heterogeneous sources of information, possibly in real time [43]. This means that, when an emergency happens, there is a need to find and exploit the information generated by different remote sensing instruments and social groups. This also involves a trust issue when analyzing such information. For instance, we may need to use available (but potentially unreliable) information. In spite of this, the fusion of remote sensing with social media offers the potential to embed remote-sensing- and localization-based services and gain significant advantages from the synergistic exploitation of these readily available data sources. This provides an unprecedented and historic opportunity. In the following section, we describe several examples that illustrate current trends in the aforementioned research directions.

IV. EXAMPLES

This section describes several examples that represent success stories in the integration of remote sensing data and social network data in the context of different applications. These examples allow us to illustrate some of the concepts provided in previous sections, as well to anticipate future trends and possibilities in the integration of these different but rather complementary sources of data.

A. Monitoring Natural Disasters

The growing number of natural disasters, such as floods or earthquakes, demands the use of additional sources of information to monitor environmental variables. Although remote sensing data such as satellite images are useful for decision making, further information is required for real-time assessments. Social networks like Twitter, Facebook, and Instagram can provide information from certain locations or areas, which are not covered by sensors.

For instance, an application case study of floods in Brazil was presented and discussed in [69]. The analysis was confined to the São Paulo region, and the study involved georeferenced image data sets collected at 315 small catchments. The system developed was implemented using a Java toolkit for JSON3, while tweets were retrieved using a Java library for the Twitter application interface (API) called Twitter4j. Both the sensor data and the Twitter data were combined as a single data stream. After a detailed analysis of the stream [69], the results confirmed that social network messages were quite useful to monitor the floods. Specifically, the results showed that there were 3.6 times more flood-related messages near to flood-affected areas. Although this study was confined to Twitter messages, other social networks (e.g., Instagram and Flickr) could also be exploited.

Another case study was presented in [70], floods in the City of Calgary in Canada. At that time, there was a lack of comprehensive remote sensing coverage of the area. In order to address this issue, authoritative and nonauthoritative data were used. In this context, authoritative data refer to data coming from official sources (e.g., satellite images) and nonauthoritative data sources include data volunteered by citizens. The authoritative data comprised RGB images, SAR and LiDAR data. The nonauthoritative data included volunteered geographic information (VGI) in the form of geolocated photos, obtained from Google search engine, TweetTracker Twitter data, real-time traffic data obtained from cameras around the city, and a list of Calgary road and bridge closures, collected from an online news source. Using these sources of data, an integrated layer was created together with a flood estimation map for different dates. Several confidence weights were associated to the different sources of data (the tweets were assigned a weight of 1, photos a 2, road closures and traffic cameras a 3, and remote sensing data a 4). It is noted that the volume of tweets corresponded linearly to the progression of the flood, with a maximum number of tweets posted during the peak of the flood. There were also increases in the number of tweets after the flood event, possibly related to flood recovery and/or closure/openings of public services. This is a good example of how remote sensing, although reliable as a data source, may not be always available and can be complemented by other data sources, including social media, to provide a source of real-time and, most importantly, on-the-ground information.

B. Monitoring Urban Environments

Monitoring of urban environments can significantly benefit from the combination of remote sensing data and social network data. The specific challenges of this application are related to the rapid and constant changes of urban environments. For instance, remote sensing data can provide an initial source for modeling urban climate and phenomena like urban heat islands. However, the footprints that people introduce when using smartphones or interacting with social networks also reflect their urban behavior [71], leading to the concept of "citizen sensors." A spatial and temporal analysis of the data resulting from such interactions can provide important information for the understanding of complex urban systems.

Different sensing technologies generate data at different spatial and temporal resolutions. For instance, remotely sensed data typically have a lower spatial and a lower temporal resolution than *in situ* sensed data but comprise a more extensive coverage. On the other hand, the granularity of data from social media is not constant. However, the volume of these data is significantly increasing due to the use of smartphones. All these data sources can be integrated and synergistically exploited in urban applications [72], [73]. For instance, online social networks such as Foursquare can be used to study human movements across several metropolitan areas [74]. These studies reflect the importance of different "citizen sensor" paradigms for urban studies integrated with remote sensing data.

C. Land Cover Monitoring and Environmental Monitoring

There have been several attempts toward the exploitation of social media data and remote sensing data for land cover and environmental monitoring. In [75], Honicky *et al.* collected pollution information by using atmospheric sensors attached to mobile phones. In [76], Aoki *et al.* used vehicles to monitor air quality by deploying mobile air quality sensing platforms on street sweeping trucks. In [77], Sammarco *et al.* used a geographical search about air pollution related posts on social networks as an effective

Table 1 Summary/Categorization of Application Examples Related to the Integration of Social Media Data With Other Data Sources

Reference	Application details	Data sources involved	Description
[69]	Mapping floods in Rio de Janeiro, Brazil	Geo-referenced image data and Twitter data	Combination of Twitter data and geo-referenced image data sets to form a single data stream, whose analysis confirmed that social network messages were indeed useful to monitor the floods.
[70]	Mapping floods in Calgary, Canada	RGB images, SAR and LiDAR data, geo-referenced images and Twitter data	Combination of remote sensing and social media data to successfully provide real-time and on-the-ground information about the floods.
[71]	Monitoring telecom network activity in Udine, Italy; Amsterdam, The Netherlands; New York, USA; Madrid, Spain	Mobile network data and social media data coming from Twitter, Flickr and Facebook	Development of a fully automated workflow (based on four consecutive processing steps) to successfully monitor telecom network activity across different cities.
[74]	Study of urban mobility patterns of people in 34 metropolitan cities around the globe	Foursquare social media data; GPS data with accuracy down to 10 meters	Use of Foursquare social media data to successfully study human movements across several metropolitan areas.
[75]	Mapping of pollution information in Accra, Ghana, West Africa.	Data from atmospheric sensors and GPS-enabled smartphones	Collection of pollution information by using off-the-shelf atmospheric sensors attached to mobile phones and a synchronized GPS, using the resulting information to monitor pollution values in different regions of Africa.
[76]	Monitoring of air quality in the San Francisco Bay Area	GPS data and data from mobile air quality sensing platforms	Use of vehicles to monitor air quality by deploying mobile air quality sensing platforms mounted on the municipal fleet of street sweeping trucks in San Francisco.
[77]	Mapping air pollution in large cities over three continents	Precise temporal and geographical metadata along with Twitter data	Use of time series made up of posts returned by a geosocial search to predict next pollution values in large cities located in different continents.
[78]	Mapping pollution in traffic in Hong Kong and Guangzhou	Data from advanced traffic monitoring systems and Sina Weibo (Chinese Twitter data)	Development of an automatic methodology to search for posts that were related to air pollution in any of the following four categories: (a) pollution, (b) weather, (c) traffic, or, (d) health, and exploitation of the resulting data for monitoring pollution values in the cities of Hong Kong and Guangzhou.

air-impurities measurement and utilized it to predict pollution values, and Tse *et al*. [78] verified the feasibility of sensing air pollution from social networks and of integrating such information with real sensor feeds. To the best of our knowledge, there has been little research on comprehensive environmental quality monitoring through the combination of remote sensing and social media data and this represents another research area in which significant advances are expected in upcoming years. For comparative purposes, Table 1 provides a summary/categorization of some of the application examples discussed in this section, indicating the data sources used and other relevant parameters.

V. CONCLUSION AND FUTURE RESEARCH LINES

In this paper, we have provided an overview of the role of localization and spatial technologies in remote sensing techniques and applications. The paper first addresses the relation between localization techniques and spatial technology (specifically pointing out their similarities and differences) in the context of the existing interrelations between remote sensing, GIS, and big data. Then, it describes the basic location analysis techniques for social media content and some practical examples specifically addressing the use of location-oriented social media content in combination with remote sensing data. As social media have become more localization aware, significant possibilities can be already seen in these examples for the integration of localization and spatial technologies (including remote sensing). From the examples presented and discussed, it can be concluded that the convergence of remote sensing and social media data will continue to transform these technologies in fundamental ways. In this paper, we have identified several topics that illustrate some important advances that can be gained from the integration of these heterogeneous sources of information. Future developments will be conditioned by the growing interest in related topics such as the Digital Earth, social media, big data, and cloud computing. ■

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