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The Potential for using Volunteered Geographic Information in Pervasive Health Computing Applications

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Abstract Volunteered Geographic Information (VGI), or geospatial crowdsourcing, is where citizens (volunteers) contribute data and information about the earth and environment that is explicitly or implicitly georeferenced and then disseminated via collaborative projects such as OpenStreetMap or social media such as Flickr, Twitter, and Facebook. VGI popularity is due in no small part to citizens making use of consumer devices, such as smartphones, to collect increasingly precise locational information and other environmental information. In this paper we describe the potential for using VGI in pervasive health computing applications. Pervasive health computing strives to provide healthcare (services or information) to anyone, at anytime, and anywhere by removing constraints of time and location. We use the OpenStreetMap (OSM) project as a case-study of a very successful VGI project. We analyse the strengths of OSM, its current applicability to pervasive health computing, and if it is a sustainable option for use as a source of spatial information for pervasive computing technologies, particularly in areas where access to information on healthcare services is limited or difficult. The paper closes by summarizing the advantages and challenges of VGI integration into pervasive health computing and outlining some of the key issues where further cross-disciplinary research is required.

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1 Introduction

The convergence of the processing capability of the personal desktop computer and the communication attributes of the mobile phone has created a powerful, Internet-connected, mobile personal device [19]. These devices have created opportunities for citizens using these devices to interact with each other, form collaborative groups, collect and disseminate information about their social networks and the world around them, in real-time. In the domain of GIS (Geographical Information Science) Volunteered Geographic Information (VGI) is a "hot-topic" for research and a recent phenomenon which is growing rapidly in terms of citizen adoption and volume of data/information generated. Citizens, using devices such as GPS receivers and smartphones can collect geographic information explicitly (by physically collecting the data themselves) or implicitly (by sharing geo-coded photographs and videos or geolocating their messages on social media such as Facebook or Twitter). "Pervasive computing technology" is not very well-defined as a technology. However, like GIS, it is a multidisciplinary research area involving technologically oriented research in areas such as hardware, communication technology, embedded hardware and software, software infrastructures, sensor technology, distributed computing, computer-supported cooperative work, human computer interfaces, sociological studies of the use of technology, etc. [38]. Reddy [60] remarks (and echoed by Prakash and Naveen [56]) that pervasive computing, also referred to sometimes as ubiquitous computing, deals with the idea of making "computing power" available anyplace, anytime in a uniform way so that it may be exploited for meeting the challenges faced by society. Healthcare is a promising but challenging application of pervasive computing [53]. Orwat et al. [53] discuss issues in the adoption of pervasive computing in healthcare. Patient privacy and technology adoption are amongst the most important issues. However the financing of pervasive computing in healthcare is also an issue. In most domains access to high quality, spatially and temporally up-to-date data is often difficult and compounded by the financial cost of access or purchase of the data.

Conway and van Lare stress that access to data for researchers, scientists, policy-makers etc. is needed to improve the public's health [11]. They state the three most serious barriers to improved access to data are: the cost and timeliness of data access, complex access models, and lack of aggregation of diverse health data resources into usable forms. This paper will explore the potential for the Volunteered Geographic Information (VGI) community to improve data access and management in the field of pervasive health computing. At the time of writing we are not aware of any work in the pervasive health computing field that is using VGI as its principal source of data and information. However research (reported below) is being carried out on prototype applications using different forms of VGI. The research contributions of this paper are as follows:

1. We outline the current forms of VGI, how they are captured, and their use in health care informatics;
2. We outline the OpenStreetMap project, which is the most popular VGI project on the Internet, and show the specific emphasis in OSM on healthcare information;
3. We outline ways in which VGI could be integrated into future pervasive health computing applications and services.
4. We provide a discussion of the challenges and issues that must be considered before VGI can be integrated into future pervasive health computing applications and services.

To our current knowledge this is the first paper of its kind to outline how the domains of VGI and pervasive health computing can be linked and how VGI can become a source of spatial data and information for pervasive health computation. This journal paper extends an earlier paper on this topic by Mooney and Corcoran [44]. The paper is organized as follows: In Section 2 we provide an overview of the literature in the area of pervasive health computing where volunteered information is used as a source of input data. In section 3 OSM is introduced as it is the most popular source of VGI on the Internet today. Advances in sensor technologies now offer citizens the possibility to measure, collect, and contribute data and information on many aspects of their everyday lives. Section 4 outlines an integrated model for citizen-centric sensors and the potential types of volunteered information that could be captured by these sensors. The final section of the paper is section 5. In this section we summarize the contributions of the paper, outline some key advantages and disadvantages of using VGI in pervasive health computing, and identify some improvements to OSM which are required to improve the potential for integration into this research domain.

2 Literature Overview

Our literature review is organised into three sections. Additional literature relating to the use of sensors for VGI is discussed in Section 4. The literature review is almost exclusively focused on the use of the Internet (and Internet-based services) for health informatics and research. Zarro [72] comments that healthcare consumers in the United States are increasingly turning to the Internet for health information and advice. A majority of Internet users in the United States use the Web to find healthcare information for themselves or others. They are collaborating with other consumers in ways that were impossible before the advent of broadband Internet availability. Kelly [47] remarks that in the UK, social media, mainly Twitter, was used by 40% of health organisations in 2010, and is mostly specifically aimed at prevention of infectious diseases. Normally health organisations mainly use web technology for one-way, expert-led communication. Yet, Kelly comments that health information, opinion, and advice are also created, owned, and shared informally by the public. Based on this Section 2.1 deals exclusively with literature outlining the use of Twitter as a source of volunteered information for health-related applications. Section 2.2 summarises some key literature on using search engine databases to extract patterns of behaviour of people searching for health-related information. This literature overview closes with section 2.3 where additional uses of Web 2.0 services and technologies are used in a health-context.

2.1 Twitter as a health information source

We found that the Twitter short messaging social media service is probably the most popular form of volunteered information currently being considered by researchers in pervasive health computing. As stated above by Kelly in the UK, social media, mainly Twitter, was used by 40% of health organisations in 2010 [47]. Boulos et al. [4] comment that social networking is useful for gleaning the collective "impression of the masses" regarding current matters, events and products. Lampos and Cristianini [41] derived rates of flu occurrences in the UK by text-mining of georeferenced Twitter messages using the open data interface to Twitter. Whilst this approach does not actually compute the "true" rates of flu occurrences the authors conclude that their approaches "gives an early warning in various healthcare situations". Kostkova et al. [39] conclude that "the potential of social networking system for early warning systems and for better understanding public concerns about their health is enormous" due to the near ubiquitous use of social media by a large percentage of the population. In Takahashi et al. [65] the authors describe the development of a method to extract information from "tweets" on Twitter and using this information generate a "hay fever" map similar to a weather report map. The study was carried out using Japanese Twitter. The identification of Japanese language tweets was crucial as less than 1% of tweets containing key words such as "hay fever" contained geolocation information. Their results showed that there was a positive correlation between pollen data and tweet data and that Twitter has the possibility of being used as a real-world sensor at least in a particular area such as hay fever. Okazaki and Matsuo [49] also perform contextual analysis of tweets from Twitter to develop an earthquake reporting system using Japanese tweets. Because of the numerous earthquakes in Japan and the numerous and geographically dispersed Twitter users throughout the country, it is sometimes possible to detect signs of an imminent earthquake by monitoring tweets. However, strictly speaking, the system does not predict an earthquake but rather informs users very promptly that earthquake activity has been encountered.

In the work by Bifet and Frank [3] the authors present a model of "sentiment analysis" where the task is to classify Twitter messages into two categories depending on whether they convey positive or negative feelings. Smileys or emoticons are visual cues that are associated with emotional states. Monitoring these coefficients may be an efficient way to detect changes in the population's opinion regarding a particular topic or brand or even in regard to government health policies. Hannon et al. [32] remark in their work that whilst Twitter provides a great basis for receiving information a potential downfall lies in the lack of an effective way in which users of Twitter can find other Twitter users to follow. This has implications for the effective dissemination of information on Twitter.

Prier et al. [57] discuss the difficulties in identification of public-health related conversations in large conversational datasets like Twitter. Their study examines how to model and discover public health topics and themes in tweets. Tobacco use is chosen as a test case. Using a machine learning generative probabilistic model for conversation text their results indicate that Twitter conversations can be a "potentially useful tool to better understand health-related topics, such as tobacco". Similar to the work of Bifet and Frank [3] Prier et al. also mentions that these context-aware text analysis models for Twitter can help public health researchers identify both positive and negative health behaviours. Murthy et al. [48] analyse a very large database of tweets retrieved from Twitter for the purposes of analysing networks related to cancer treatment and recovery. The authors indicate that visualisation of these networks and visualisation of these large databases of social media information is a crucial area for future work. As outlined above - accessing large quantities of tweets from Twitter is reasonable straightforward. However, it is the case that comparably few users actually geocode their tweets meaning that results (such as identification of flu incidences) cannot be accurately referenced spatially. The next section of the literature review investigates ways the usage patterns of Internet search engines can be used to extract useful behaviour patterns.

2.2 Search Engine Analysis

When we use a search engine such as Google or Bing we are implicitly volunteering information through the search terms we provide and the search results links we follow. Eysenbach [21] introduces and defines his own term *infodemiology* as "the science of distribution and determinants of information in an electronic medium, specifically the Internet, or in a population, with the ultimate aim to inform public health and public policy". Marsh et al. [43] introduce their terminology of "Collective Health Intelligence" where by using the Internet, millions of people in the course of their daily activities contribute to "data and information stores". This can be extended to patterns of choices and actions in online shopping, discussion forums, etc. "Collective Health Intelligence" harvests these information stores and the results of which "could enhance the social pool of existing health knowledge available to the public health agencies" [43]. Breyer et al. [5] combine meteorological data for Seattle and New York with Internet search volume activity for kidney stones in Google Insight. They find a very strong correlation with temporal and regional kidney stone insurance claims data. The ambient temperature in Seattle and New York were compared with search volume for these regions to display qualitative relationships. Breyer [5] correlated information extracted from Google Insights for Google Search data with hospital admissions. Breyer found that "Internet search volume activity for kidney stones correlates strongly with temporal and regional kidney stone insurance claims data". Conrad [10] provides similar results by analysing influenza-like illness (ILI) data from the U.S. Centers of Disease Control and Prevention, and anonymized, aggregated Google search query data. Conrad concludes that a rise in the frequency of certain influenza-related search terms in a location corresponds with a rise in actual flu activity for that location. Collier et al. [9] developed BioCaster. BioCaster is an ontology-based text mining system for detecting and tracking the distribution of infectious disease outbreaks by continuous analysis of documents reported polled from over 1700 RSS feeds. The text information in these feeds are then classified for topical relevance, geocoded, and plotted on web-based maps. A large, freely available, ontology is used to map "layman's terms" to formal medical terminology.

2.3 Additional Web 2.0 related literature

In this section we provide some interesting examples from the literature of the use of volunteered healthcare information from sources other than Twitter and Internet search engines. Kim et al. [37] characterize major topical matters of H1N1 questions and answers raised by the online question and answer community Yahoo! Answers during H1N1 outbreak. Friesema et al. [26] show results from five years of study in the Netherlands from an internet-based system monitoring influenza type illness during the winter season was developed. On a weekly basis participants filled out a short online questionnaire asking about cough, running nose, body temperature, etc.. In case symptoms are reported, the participant is also requested to report whether or not a GP was consulted, and whether or not daily activities were adjusted due to the symptoms. While their sample size was small the authors conclude that this approach "seems useful for early detection of changes in incidences of influenza type illness". In an example from Taiwan, Syed-Abdul et al. [64] describes where Facebook discussions were monitored by the Ministry of Health. After monitoring these discussions the Minister promised to initiate dialogue with the Bureau of National Health Insurance on organisational issues affecting emergency departments and vowed to provide more resources for hospitals to improve emergency-room overcrowding and quality of care. Gray et al. [28] outline results of a study of adolescents using Internet search engines for health information. Their results show that adolescents do perceive the Internet as an alternative information source for health problems and in some cases use it to "avoid a visit to a health term professional". The participants in the study recognised that Internet information may not be credible so they combined results from several searches and sources. Zarro [72] remarks that the tags assigned by an individual are visible to other users in most collaborative websites and projects. This results in a peer-created knowledge organization system of information resources. Tags can be created by the user solely for their own use, yet the community benefits from the aggregation of individual efforts. The Web 2.0 model of open collaboration have seen peers emerged as "guides" to health information. Finding credible, high-quality, and comprehensive health information is a continued challenge caused by the health literacy and vocabulary gap between clinicians and laypersons tagging and organising pages and content in health information sites.

This section has outlined literature from the domain of health informatics which documents software and services which consume information available on the Internet. In the next section we introduce OpenStreetMap (OSM), the most popular example of Volunteered Geographic Information (VGI) on the Internet today.

3 VGI Case-study: OpenStreetMap

In this section we introduce OpenStreetMap (OSM) [50]. OSM is a project with the mission of creating a free world map. Members of the OSM community (contributors) collect spatial data on roads, railways, rivers, forests, homes, etc. and make this data freely available to the OSM project. It is one of the only global multi-contributor databases that releases changes and updates instantly. There are no limitations on map attributes. Contributors can use a predefined ontology or invent attributes for features. In this section we describe the VGI community in OSM. We also show the types of health related information currently in OSM and how this could potentially be extended to include more precise and specific information.

3.1 The VGI Community in OSM

The VGI community is a global crowdsourced (many volunteers working together) community which shares many similarities with the Wikipedia model of information collection. The OSM project [51] is a crowdsourced geospatial database with volunteers all over the world. Masses of contributors from around the world are volunteering their time and efforts to collaboratively create a detailed base map. Many other volunteers in OSM are working on: software development for OSM, maintaining the OSM Wiki website, organising mapping party events, etc.. Volunteered Geographic Information (VGI), the term coined by Goodchild [27], is the recent empowerment of citizens in the collaborative collection of geographic information. He argues that VGI has enormous potential to become a "significant source of geographers' understanding of the surface of the Earth". Crucially, "by motivating individuals to act voluntarily, it is far cheaper than any alternative, and its products are almost invariably freely available". Spatial data is contributed to OSM from: portable GPS devices, tracing shape outlines from aerial photography, import of free spatial data, or simply from local knowledge [8]. Ciepluch et al. [6] and Haklay and Weber [30] provide detailed introductions to the OSM project.

The crowdsourced approach of OSM derives its success from citizens mapping and collecting data and information about their locality. Features being mapped include the location of garbage cans, pedestrian crossings, land cover types, shops, education facilities, to government buildings, roads and river networks. All data in the OSM database can be downloaded for free in a variety of spatial data formats. Additionally a number of open source tools are available to process this data and produce other formats such as Google Earth-friendly KML. Ormeling [52] argues that OSM provides an unprecedented opportunity for anyone to "create the maps that they want when they want". A core motivation behind the production of VGI is likely the inaccessibility and cost of accurate sources of geographic information [31, 74].

3.2 Health related information in OSM

In this section we provide some examples of health related data and information contributed to OSM. It is often interesting and informative to take a snapshot in time of the OSM global database to understand the rate of growth of specific feature types on a global scale. In Table 1 we show a summary of the overall growth in the volume of health and healthcare related points and polygons in the OSM global database. We show the 6 most frequently occurring "tags" OSM contributors apply to points or polygons representing healthcare related or health service related features. In the six month period from 10^{th} February 2011 until 13^{th} October 2011 there has been an overall growth of 36% in the number of points and polygons representing healthcare. Point geometries are used to denote the location of a doctor's surgery or dentistry as a Point-of-Interest in OSM or as a supplement to the polygon representing the building outline of the same feature. Individually, in Table 1 the greatest rate of growth over this period have been for "emergency" (68%) and "healthcare" (59%). The "healthcare" tag can indicate facilities providing access to doctors, dentists, physiotherapists, occupational therapists, etc. The "emergency" tag can be used as both an access restriction on roads to indicate that it is usable by emergency vehicles or for hospitals to indicate whether or not they have emergency facilities (called "A&E" (UK and Ireland) or Emergency Room (United States)). Figure 1 shows a plot of the rate of increase of contribution of points (Points-of-Interest) features representing Pharmacys and Hospitals in the OpenStreetMap database for Ireland the United Kingdom between 2007 and June 2011.

Table 1 The usage of healthcare related information and service tags in the global OpenStreetMap database. The overall rate of growth in the number of these tags between Feb 2011 and October 2011 is shown

Feb 2011	**Total**	**Points**	**Polygon**
Emergency	6,403	509	5,880
Dentist	9,461	8,976	484
Hospital	59,912	48,033	11,719
Pharmacy	49,719	47,978	1,740
Doctor	12,665	10,404	2,249
Healthcare	967	840	126
Total Feb 2011	139,127	116,740	22,198
Oct 2011	**Total**	**Points**	**Polygon**
Emergency	10,227	1,448	8,754
Dentist	11,801	10,974	825
Hospital	83,111	65,185	17,630
Pharmacy	64,589	61,559	3,027
Doctor	17,891	14,249	3,615
Healthcare	1,626	1,307	316
Total Oct 2011	189,245	154,722	34,167
Overall Increase	36.02	32.54	53.92

3.3 Extending OSM's health-related data model

As outlined in Table 1 the "amenity" tag has a number of important values relating to healthcare. However

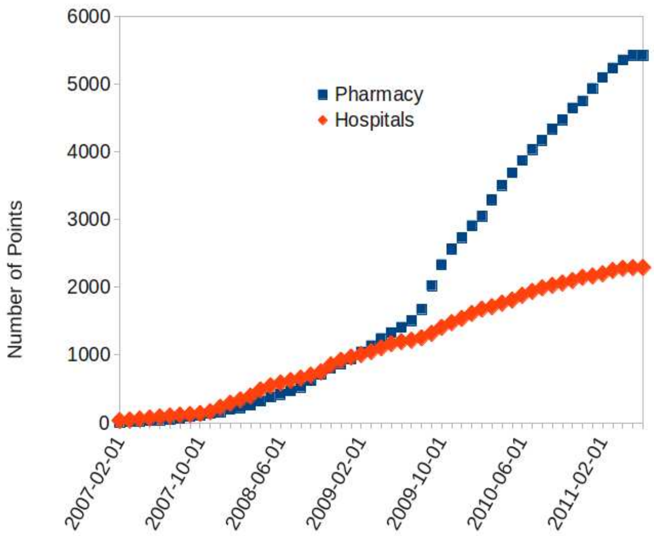

Fig. 1 Analysis of the entire history of contributions to OpenStreetMap in the United Kingdom and Ireland shows the rate of increase of contribution of points (Points-of-Interest) features representing Pharmacys and Hospitals

Fig. 2 A screenshot of Dublin city center (Dublin 1 and Dublin 2), Ireland - October 2011 from openstreetmap.org

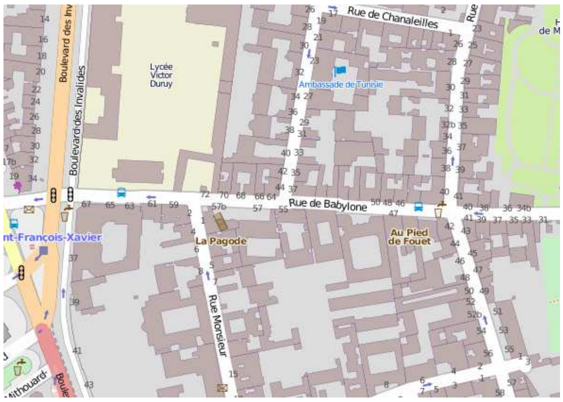

Fig. 3 A screenshot of 7^{th} arrondissement of Paris, France - October 2011 from openstreetmap.org

some of these tags are too broad in their definition. For example "amenity=healthcare" is not specific to the type of healthcare provided. Individuals and groups can propose extensions to the OSM data model in order to model some physical or geographical feature (and their attributes) in greater detail. This provides communities or groups with the opportunity to propose extensions of the OSM data model which will allow them to contribute their spatial information to OSM. One such proposal is that addition of keys specifically related to objects describing health care/public health/services. These can be viewed on the OSM Wiki pages [23]. The information on these proposals are subject to change. In one sense the current overloading of keys such as `amenity` to describe healthcare and other diverse functions works well in OSM. There are no requirements that the contributors to OSM have very detailed knowledge of the building, facility, or service they are mapping. The expectation is that these contributors will use the accepted tagging ontology provided (as outlined in OSM Map Features Wiki [54]). As Stvilia and Jorgensen [62] conclude, tagging must always remain an activity the contributors to social media *want* to carry out. In OSM, provided contributors choose tagging from the accepted ontology of tags, all OSM map rendering software can interpret the key values and label the output map accordingly. Overloading of the certain keys for health could lead to a situation where the area of health related services are simplified, for tagging purposes, too severely. This new healthcare extension proposal in OSM provides support for: tagging objects in a detailed way for support groups, counselling centres, health related services; the real relationships of a hospital and its functions; prevention facilities such as counselling centres (and their area of practice such as drugs, crisis, sexual abuse, or rehabilitation) or community driven services such as support groups. While on first glance this may appear as if greater tagging burden is being placed on contributors to OSM the advantages of such a detailed and specific approach are numerous. More advanced types of healthcare applications could be developed based upon the free and open availability of such detailed spatial information.

3.4 Using OpenStreetMap as a VGI source

The OSM global database of VGI is growing rapidly. However the coverage of the spatial data in OSM is not always homogeneous. Figure 2 shows a screenshot of the "Mapnik" map rendering of OpenStreetMap data for Dublin city centre, Ireland, on openstreetmap.org from October 2011. There is good overall coverage and considerable location-based information regarding hotels, transportation, and street-names, etc. This contrasts with the map in Figure 3 showing the "Mapnik" rendering for the 7^{th} arrondissement of Paris, France also during October 2011. The key difference is the greater spatial detail for building outlines and building street addresses also visible. Whilst this is only a visual comparison it highlights differences between OSM representations of different urban regions while also demonstrating a potential under-representation of the urban landscape in the case of Dublin. As outlined by Over et al. [55] there are urban biases in the collection of VGI. This presents a problem for rural areas and communities where such geographic regions may not even be represented in VGI databases. But as the two screenshots demonstrate, in Figure 2 and Figure 3, there is also differences in representation and coverage between urban areas. Mooney et al. [46] remark that there are no accepted metrics for measuring the quality of OSM or to a wider extent the quality of VGI. Given the dynamic and organic nature of the spatial data contained in the OSM databases the quality of the spatial data can change quickly [45]. For OSM to become a more attractive option to pervasive health computing researchers as a source of spatial data and a web-based mapping system issues of quality and coverage must be addressed.

In the next section we look at VGI generated from different types of sensors. For each classification of sensor we provide some examples from the literature of their implementation and usage.

4 VGI from Sensors

VGI is not restricted to spatial data which has been explicitly collected by citizens and contributed to OSM or similar projects. The potential of citizens to monitor the state of the environment, validate global models with local knowledge, and provide information that only humans can capture is vast and has yet to be fully exploited [15]. In this section we discuss the integration of VGI data from fixed and mobile sensors. This integration model is presented in Figure 4. We have created a high-level organisation of potential sources of VGI from fixed and mobile sensors. We classify sensors into four groups: fixed autonomous sensors, mobile autonomous sensors, fixed user operated sensors, and mobile user operated sensors. Our model is restricted to individual sensors rather than large networks of sensors deployed over a large geographical area and which are beyond the scope of our paper. In some cases APIs, download services, and visualisation services are available for integrated sensor data and information. In the next sections we will outline examples of sensors or applications in each of these four classes.

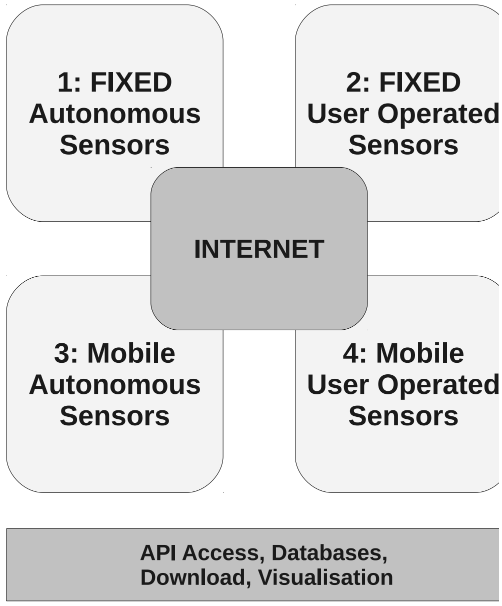

Fig. 4 VGI data collection from fixed and mobile sensors

4.1 Fixed autonomous sensors

Fixed autonomous sensors are "installed" into a fixed position and usually run completely independent of user input. These include: electricity consumption meters, humidity and temperature measurements, water flow measurements, data about the status of home appliances (water consumption, heating appliances). Examples include:

- Schoofs et al. [61]: **Household Power Consumption:** A system to automate electricity data annotation leveraging cheap wireless sensor nodes.
- Drumea and Svasta [18]: **Temperature and Humidity Monitoring:** Measurement and construction aspects of sensors for temperature and humidity designed using battery powered wireless sensors coupled with a low power microcontroller and a radio subsystem.
- Wang et al. [68]: **Ambient air quality and Carbon Monoxide monitoring**: The sensor systems, combined with a wireless communication network, give the benefit of convenience in deployment, and lower operation and maintenance cost. The sensor nodes can be powered by either batteries and/or solar energy sources.

4.2 Mobile autonomous sensors

Mobile autonomous sensors can be moved at regular intervals or are constantly moving. These can include: flying Unmanned Aerial Vehicles (UAV), noise monitoring on smartphones, temperature monitoring on smartphones, data about traffic and automobile performance using ODBII (On-board diagnostics). Examples include:

- Thiagarajan et al. [67]: **Traffic congestion analysis:** Smartphones can provide location estimates using a variety of sensors - GPS, WiFi, and/or cellular triangulation. The authors develop software that samples position from drivers' phones to monitor traffic delays at a fine spatiotemporal granularity.
- Sun et al. [63]: **Using UAVs for capture of remotely sensed imagery** moving object detection (cars on roads, ships in rivers, etc) in aerial images captured by a low-cost Unmanned Aerial Vehicle.
- Rana et al. [58]: **Noise Monitoring:** Microphones in previous mobile phones can be configured to measure the surrounding noise level and give insights about the nature of contextual events. The data collected are then used to build representative noise pollution maps to enable specialists to understand the relationships between noise exposition and behavioural problems.
- Lee et al. [42]: **Vehicle Performance:** All cars and light trucks built and sold in the United States after January 1, 1996 are required to be equipped with On-Board Diagnostics II (OBD-II). Lee et al. use OBD-II information for prediction method of fuel consumption (and subsequently emissions).

4.3 Fixed user operated autonomous sensors

Fixed user operated autonomous sensors include sensors which are installed in a fixed location but require a user to "switch-on". The "switch on" can be performed over to web using a simple web interface or using some physical switch on a microcontroller. Data logger sensors without a permanent connection to the Internet must store their captured data on-board until the user connects them to the Internet for upload. Examples include:

- Alfa et al. [2]: **Rainfall and Water resource management with data loggers**: Alfa et al. develop temporal distributions as well as spatial variability of rainfall for the Densu River basin in Ghana by using data loggers. These are used to determine the duration pattern of rainfall events and their intensities and how these affect the partitioning of rainfall into overland flow and infiltration.
- Williams et al. [70]: **Solar Energy Production:** Using highly programmable data loggers the authors show how the energy provided by solar home systems can be monitored more accurately.
- Zhou et al. [73]: **Smart Patient Monitoring:** The authors propose a personal diabetes monitoring system which integrates wearable sensors, 3G mobile phones, Google Health to facilitate the management of diabetes. The wearable sensors and 3G cellular phones automatically collect physical signs, such as blood glucose level and blood pressure allowing users, especially seniors citizens, to conveniently record daily test results and track long term health condition changes regardless of their location.

4.4 User operated mobile sensors

User operated mobile sensors almost exclusively include devices such as smartphones, PDAs, etc. The user is moving in both space and time. For example they can capture and contribute geocoded photographs and geocoded video, locational information using GPS, geolocated tweets or check-ins (such as Foursquare). An example is illustrated in Figure 5. Examples of user operated mobile sensors include:

- Hollenstein and Purves [33]: **Geocoded Photographs:** Hollenstein and Purves describe the results of harvesting georeferenced and tagged metadata associated with eight million Flickr images and draw conclusions on how large numbers of people name and describe downtown city areas. The results of this work could be applied to analysis of tagging of photographs of natural or environmental disasters or incidents relating to public health such as forest fires or industrial accidents.
- Lampos and Cristianini [41]: **Geolocated Tweets:** Lampos and Cristianini derived rates of flu occurrences in the UK by text-mining of georeferenced Twitter messages using the open data interface to Twitter.
- Curtis and Mills [12]: **Geocoded Video:** A spatial video application was developed and used to collect data from the post-disaster landscape of Tuscaloosa, USA, which was hit by a large tornado in April 2011. This video, once processed, can be viewed within a Geographic Information System which combines street-level images with exact location. These data can be used to support ongoing recovery efforts,

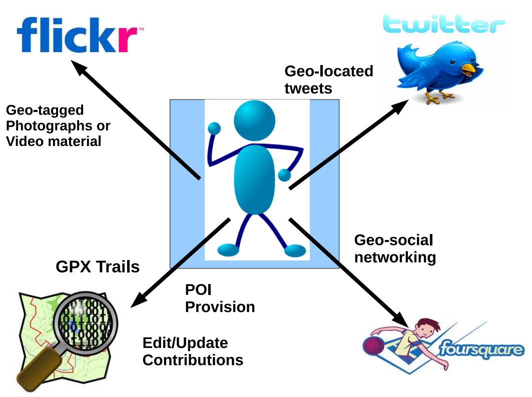

Fig. 5 The citizen content generator exclusively from social networking services in Web 2.0 and OpenStreetMap. Taken from Mooney and Corcoran [44]

while also archiving a dataset suitable for the spatial analysis of the changing post-disaster landscape.
- Wright et al. [71]: **"Self-sensing"**: Citizens often freely share the digitally collected information about themselves not only with their immediate friends and family, but often with "friends" on the Internet or even the public at large. The Nike + SportBand for runners allows one to "compete" with others over the Internet. Location-based services such as Foursquare ([24]) make it a game to become a mayor of parts of your city or environment by sharing the places you go most often and writing reviews on them.
- Jacob et al. [35,34]: **Haptic-sensors:** In both works the authors make use of the haptic (touch) sensors on smartphones as a means of providing non visual/oral feedback in software applications such as pedestrian navigation and in-vehicle passenger information provision.

In Figure 4 data capture rates can range from: every few seconds (for example ODBII, electricity metering and power consumption), minutes (geocoded photographs, Twitter feeds), hourly (air quality measurement, humidity, etc), or daily (GPS loggers, geocoded photographs, UAV captured aerial imagery). The bottom of Figure 4 shows the means by which other applications and researchers can access the information produced by the sensors outlined in the previous sections. In Figure 5 an example of the citizen generating VGI exclusively using social networking services in Web 2.0 and OSM is shown (from Mooney and Corcoran [44]). The citizen, in this figure, is using only their mobile smartphone.

4.5 The near future for VGI sensing

In the near future citizens will not have to always physically collect data themselves and then submit this to VGI initiatives. As shown in Figure 4 user operated mobile sensors will allow citizens to contribute their knowledge of subjects or areas by direct collection of this data from their own personal sensors. One of the most prominent examples of this is in the United States. Bikestatic [59] is built around a microcomputer computer installed in rear wheel of bicycles in bicycles available on rental schemes in certain cities. Users of these bicycle contribute data implicitly. In addition to logging traces of the journey Biketastic obtains information about road roughness and noise levels using accelerometers and microphones which are now common on smartphones. Based on this information contributed by users, in real-time over 3G cellular networks, it is possible for researchers to measure real-time noise levels, traffic congestion, road condition, etc. Health researchers may investigate issues such as pollution etc. using proxy-indicators such as noise and congestion information. The field of geosensors, which will provide sensors available for everyone to use at affordable prices will increase again, by several orders of magnitude the amount of data available.

In Kularatna et al. [40] the authors developed gas sensors capable of detecting the presence of gases, at levels which are dangerous to public health, in the air. The gas sensors are connected together using a micro converter which sends data to a data acquisition card installed in a computer. This low cost solution was adequate and performed well in trials allowing measurement of gases with using off-the-shelf components and standard desktop computers. In the work by Kularatna et al. [40] gas sensors were developed which communicated with a desktop computer as client and then to a server machine. The sensor landscape is changing rapidly. Ding et al. [17] presents a solution of nuclear radiation monitoring based on GPS-enabled wireless sensor networks. The proposed nuclear radiation detection nodes are of minimum size while still ensuring the good overall quality in communication, sensing, localization and calculation. These nodes are small enough to be installed indoors or outdoors as well as to be mounted on mobile equipments. Karan et al. [36] present a novel approach for diagnosing diabetes using pervasive healthcare computing technologies by embedding the heavy computation functionality on the client device (in this case smartphone/PDA) rather than exclusively on a server. Ding et al. [16] comment that the concept of "smart-homes" is now a reality due to the the availability of inexpensive low-power sensors, radios, and embedded processors meaning that "smart homes" are typically equipped with a large amount of networked sensors which collaboratively process and make deductions from the acquired data on the state of the home as well as the activities and behaviours of its residents. Today's sensors attempt to collect their data autonomously without need for client computers. The sensor device prepares that data, potentially performing some calculation or analysis, before sending this data to some server environment over an Internet link. The capabilities of sensors have not greatly changed between today and say two or three years ago. However the key difference is the lowering of operational costs due to lower power consumption, by using micro-controllers, lower overall cost of sensor device construction, and sensing capabilities of smartphones (GPS, accelerometer, etc) [16]. The combination of these factors may turn out to be critical for the future of VGI. If citizens are motivated to contribute data or information they will expect an environment where there should be low cost of entry (purchase of equipment) and ultimately low running costs. This could become a crucial issue relating to whether citizens decide to contribute their data for VGI community projects.

5 Discussion and Reflections

In this section we provide some concluding remarks and outline advantages and disadvantages of using volunteered information in a pervasive health computing context. This paper has provided an overview of the use of volunteered information in pervasive health computing, how volunteered geographic information (VGI) could potentially be used, and finally how citizen-centric sensor technologies could increase the amount of data and information openly available for pervasive health computing applications. There were a number of research contributions delivered in this paper. In section 2 we have provided a detailed overview of literature in the pervasive health computing field with emphasis on volunteered information sources. This included research work on using messages from the Twitter service, analysis of usage of Internet search engines, and other Web 2.0 services and tools such as Flickr and RSS feeds. Section 3 introduced the OpenStreetMap (OSM) project in detail. OSM was chosen because it is the most popular example of VGI on the Internet today. In Section 3.2 we outlined the types of health-related information currently available in the OSM global database. Whilst OSM is a very large VGI project (in terms of number of contributors and volumes of data) we envisage OSM as one key component in an interconnected model of data and information sources volunteered by citizens using sensor devices. In Section 4 we discussed a classification of VGI from both mobile and fixed sensors, shown in Figure 4. There is an immediate requirement that the research communities in GIS/VGI and health informatics provide examples of successful integration of VGI and health data/information to assist in validating the approaches outlined in this paper.

5.1 Using VGI in Pervasive Health Computing

In the next two sections we outline the advantages and disadvantages of VGI to pervasive health computing.

5.1.1 Advantages

Deshpande and Jahad [14] powerfully outline the changing landscape in healthcare information. No longer are the public simply just passive consumers of information. The public now have the tools to manage knowledge, answer questions and find services in a way that is bypassing and even exceeding the capacity of the traditional establishment and its gatekeepers. Deshpande and Jahad [14] remark that those citizens belonging to the M (Millennial or Multitasking or Multimedia) Generation (born between 1982 and 2000) are already tuning out their predecessors, thanks to tools such as instant messaging services, blogs and podcasts. Willard and Nuygen [69] agree that using new data sources such as publicly available Internet search trend data has long-term utility in many types of health research. Useful applications could include real-time disease surveillance, use as an exploratory tool before designing more involved studies, estimating the occurrence of less common diseases or conditions, and for better understanding of patients' priorities [69]. As the Internet becomes more pervasive in society and central to patients' health information-seeking behaviour, "the accuracy and utility of these tools will likely increase, highlighting the importance of improving our understanding of the strengths and limitations of using them for medical research". Clarke et al. [7] outline the advantages in using VGI/spatial data tools in health informatics. Using spatial data tools such as Google StreetView available on the Internet can provide health researchers with a "virtual audit instrument for geographical areas which can provide reliable indicators of recreational facilities, the local food environment, and general land use". The update frequency of spatial data in OSM makes it an exciting prospect as a "virtual audit instrument" in this type of application. The dynamic nature of the OSM data would provide researchers with a constantly evolving picture of a given local environment. Crucially, Clarke et al.

[7] stress that these potential applications can "significantly reduce the costs of collecting data objectively and do so in an unobtrusive manner". The conclusion of Eysenbach [22] is an emphasis on the "open" philosophy of Web 2.0 tools will now raise expectations of the "Facebook generation" in terms of dealing with health related data. The "Facebook generation" are those whom have been using social media sites and applications for many years. Eysenbach [22] comments that "Web 2.0 savvy consumers will push the envelope and demand more than just a health information portal which allows them to view or access their data but not to do anything else with it". He claims that citizens will demand full control over their data with potentially, as a minimum, requirement for an XML export to their mobile or computing device.

5.1.2 Disadvantages

Data and information generated by citizens must be carefully used. Boulos et al. [4] argue that merely extracting information from social media and search engines as an indicator of public health incidents or attitudes is unreliable. They argue that each social network service on the Internet and its prevailing user characteristics such as age, gender, user locations, etc must be considered as these data can help in better interpreting any intelligence or results derived from these services. Accessing such demographic information may not always be possible. D'Amato et al. [13] investigate cases where anxiety raised by Facebook usage induced asthmatic attacks in asthma sufferers. In what is a negative side of social media usage the authors conclude that their analysis indicated that Facebook, and social networks in general, could be a new source of psychological stress, representing a triggering factor for exacerbations in depressed asthmatic individuals. Abbas et al. [1] raise concerns about the legal implications of citizens collecting spatial information, in real time. The authors argue that devices such as mobile camera phones, GPS data loggers, spatial street databases, RFID, and other pervasive computing "can be used to gather real-time, detailed evidence for or against a given position in a given context". Their primary concern is that there are "limited laws and ethical guidelines exist for citizens to follow when it comes to what is permitted when using unobtrusive technologies to capture multimedia and other data (e.g., longitude and latitude waypoints) that can be electronically chronicled". Friesema et al. [26] argue that health researchers must be careful to validate their findings from research carried out using citizen generated information and must be careful not to ignore the limitations of what they call a "crude syndromic surveillance tool in real time."

5.2 Considerations for VGI integration

In this section we close the paper with a discussion of some of the key design considerations for applications to use VGI in the future. This will also assist in highlighting all of the fundamental research aspects that need further investigation and scientific validation. As outlined in Section 4 there are four categories of sensors that could provide VGI data useful for pervasive health applications. Fixed autonomous sensors provide a constant steam of geolocated data such as ambient air quality monitoring. Mobile autonomous sensors do not necessarily provide constant streams of data but are generally linked to GPS. Examples include traffic congestion and urban noise monitoring. Fixed user operated sensors have the ability to be switched on and off by their operators and have been used for pervasive health applications such as smart patient monitoring (Zhou et al. [73]). Finally, user operated mobile sensors are probably the most common due in no small part to the smartphone and miniaturisation of devices such as GPS. VGI generated from user operated mobile sensors is probably the most easily accessible form of VGI (geolocated tweets, geocoded video, geolocated photographs, OpenStreetMap data, foursquare checkins, etc.). Yet despite the simplicity in accessing these forms of VGI they are probably the most difficult to integrate into pervasive health applications. Unlike data from fixed or mobile autonomous sensors the VGI from user operated mobile sensors requires greater understanding of the spatial resolution, geometric and temporal accuracy, metadata and attribution information, etc.

5.2.1 ***Validation of VGI***

Before VGI can be used in any serious pervasive health application it must be validated. Validation and quality assurance of VGI is still a major ongoing research question in GIS and Geoinformatics. Studies have been carried out comparing VGI to authoratative sources of spatial data. While these studies reported favourable results for geometric comparison of the data a major stumbling block remains the ability to validate attribute information in VGI. It is currently difficult and/or very expensive to obtain access to large authoritative databases of attribute data (points of interest database, urban building description databases, etc.). In the case of microblogging forms of VGI high end machine learning and text pattern matching must often be employed to distinguish certain text (such as placenames, disease types, emotion terms, etc). The ideal scenario for pervasive health applications is to access VGI which is already validated or can be readily validated using web services or APIs. At present pervasive health applications are expected to carry out their own validation on any VGI used. Murthy et al. [48] remarks that visualisation of these data and social networks is an important aspect of validation.

5.2.2 ***Spatial Coverage of VGI***

One of the problems with many forms of VGI (OSM, Twitter, citizen science reports, etc.) is that they are often very similar to authoritative sources of similar information. They are similar in that there is usually high resolution coverage for urban and densely populated areas while these is inhomogeneous coverage or reporting from rural areas, areas with small population density, or remote locations (mountain regions for example). As shown in Section 3.4 coverage of VGI can differ between high population density urban areas also with Over et al. [55] reporting that there is an urban bias in VGI. For pervasive health applications to appeal to the widest possible citizen audience inhomogeneous spatial coverage in VGI presents a major issue. A potential solution to this suggested in the literature is the augmentation of VGI with spatial data from openly available authoritative sources.

5.2.3 ***Addressing Social Issues***

VGI tends to reflect a middle/upper class view of the world almost inherently based in the western or first world. Some of the sources of VGI discussed in Section 4 are based on activities such as automobile usage or leisure pursuits such as cycling (i.e. Bikestatic [59]). It has been shown, by Haklay [29] that socially disadvantaged or deprived areas have less VGI. Clarke et al. [7] suggest using tools such as Google StreetView to "virtually audit" areas to collect information on: housing, commercial premises, etc. Many of those in socially disadvantaged areas do not see the need or benefit of using the Internet and other ICTs for pursuits such as VGI. A report from the UK Department of Communities and Local Government [25] conclude that to tackle this type of digital exclusion "digital technologies that do not require PC-based internet technology" should be utilised to reach out to those without access, skills or motivation to become otherwise digitally included. Pervasive health applications obviously address this type of need but it is an immediate requirement that VGI must be coordinated to include data and information relevant to these areas and issues. Future studies focussed on understanding the reasons for "gaps" or "whitespaces" in collections of VGI data, particularly for urban areas, are required to investigate if there are linkages to social inequality or deprivation. Recent research by Haklay [29] shows evidence that there is correlation between urban deprivation index and completeness (or coverage) of geographical data in OSM with the author speculating that one of the causes of this might be the cost of GPS loggers.

5.2.4 ***Resource requirements for VGI integration***

In this paper we have outlined the advantages of integration of VGI into pervasive health computing applications (summarised in section 5.1.1) with a discussion of some of the disadvantages in Section 5.1.2. In section 2 we showed how Twitter, search-engines, etc have been utilised in pervasive health applications. One of the most pertinent issues surrounding the usage or extraction of VGI from these technologies is the amount of resources (time, computing power, skills, etc..) which must be employed to derive useful and statistically meaningful VGI. Most of the literature reviewed in Section 2.1 indicated that Twitter could give "an impression of the feelings of the masses" [4], "provide an early warning system" for flu like illness [41], or "identify negative health behaviour". But as Takahashi et al. [65] concludes "less than 1% of tweets are geolocated" and consequently much of the analysis of Twitter databases require the implementation of advanced text mining and pattern matching algorithms to extract syntactic and semantic knowledge [66]. These are certainly not suitable, in their current state, for near or close to real time pervasive health application technology requirements. Processing of data on client devices is not always the most efficient option [36]. Analyzing the vast quantity of unstructured data from social networking applications "presents challenges for software and hardware" [20].

5.3 Conclusions

No longer are the general public simply passive consumers of information. VGI is generated and shared on the Internet by citizens using a variety of devices with smartphones and sensor technologies becoming almost ubiquitous. The update frequency of VGI can provide health researchers and organisations with a very dynamic view of the environment. This rapid update frequency and the openness of VGI also presents its greatest challenge: the verification and quality assurance of this data for purposes such as pervasive health applications. As more research is carried out on these challenges the future potential for VGI in pervasive health applications is an exciting one.

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