Spatial Computing:*
Accomplishments, Opportunities, and Research Needs

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Abstract

We present a perspective on the societal accomplishments, recent shifts, challenges, and opportunities in spatial computing based on the discussions at the 2012 Computing Community Consortium (CCC) workshop, "From GPS and Virtual Globes to Spatial Computing – 2020," held at the National Academies' Keck Center to assess interdisciplinary developments and research challenges in spatial computing. We first provide a few examples of transformative accomplishments resulting from spatial computing research. We then discuss a recent shift that has resulted from the recent integration of spatial computing technologies into the everyday lives of citizens. This integration has led to an array of new short-term opportunities in spatial computing along with new long-term research needs that must be addressed if spatial computing is to achieve its transformative potential.

1 Introduction

Spatial computing encompasses the ideas, solutions, tools, technologies, and systems that transform our lives and society by creating a new understanding of locations; how we know, communicate, and visualize our relationship to locations; and how we navigate through those locations. From virtual globes to navigation devices, spatial computing is transforming society. We have reached a point where a hiker in Yellowstone, a school child in DC, a biker in Minneapolis, and a taxi driver in Manhattan know precisely where they are, know the locations and details of nearby points of interest, and know how to efficiently reach their destinations. Large organizations already use spatial computing for site selection, asset tracking, facility management, navigation and logistics. Scientists use Global Navigation Satellite Systems (GNSS) [29], such as the Global Positioning System (GPS), to track endangered species and better understand animal behavior, while farmers use these technologies for precision agriculture to increase crop yields and reduce costs. Virtual globes [3] such as Google Earth and NASA World Wind are being used to teach school children about their local neighborhoods and the world beyond (e.g., Wini Seamount near Hawaii, extraterrestrial landscapes on Mars and the Moon, Sloan Digital Sky Survey, etc.) in an enjoyable and interactive way. In the wake of recent natural disasters (e.g., Hurricane Sandy), Google Earth's service has allowed millions of people to access imagery to help in disaster response and recovery services [24]. Within days of the 2010 Haiti

*Computing Community Consortium (CCC) workshop participants used the term "Spatial Computing" as a generalization of spatial data structures [37], spatial databases [41], spatial data mining [11], spatial statistics [13], spatial cognition [9], and other computational issues related to geographic and non-geographic spaces (e.g., sky catalogues, indoors, and VLSI design). Within geographic spaces, the term focuses on computational aspects of a multi-disciplinary area variously referred to as Geo-Informatics, Geomatics, Geocomputation, Geoinformation Science, Geographical Information Science, Computational Geography, etc. More broadly, Spatial Computing refers to the study of computing in spatial, temporal, spatio-temporal spaces across both geographic and non-geographic domains.

Table 1: Representative Spatial Computing Organizations

ACM SIGSPATIAL
International Society of Photogrammetry and Remote Sensing (ISPRS)
International Geographical Union (IGU)
IEEE Geoscience and Remote Sensing Society (GRSS)
Institute of Navigation
Society of Photo-optics Instrumentation Engineers (SPIE)

earthquake, post-disaster roadmaps were created thanks to citizen volunteers submitting to the popular volunteered geographic information [14] website OpenStreetMaps [27].

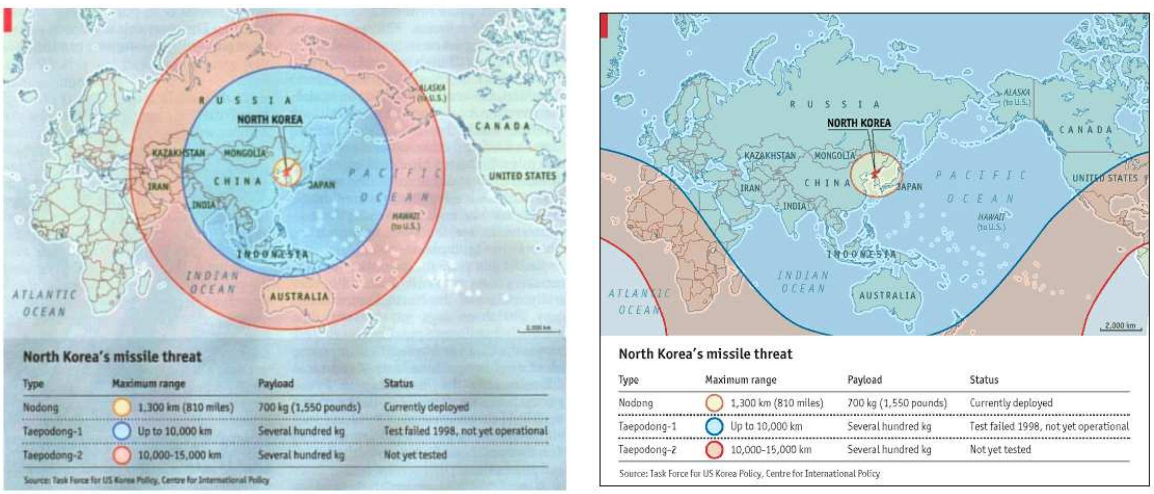
In the coming decade, spatial computing promises an array of new transformative capabilities. For example, where route finding today is based on shortest travel time or travel distance, companies are now experimenting with eco-routing, finding routes that reduce fuel consumption and greenhouse gas emissions. Smart routing that avoids left turns has already saved UPS over three million gallons of fuel annually [45]. Such savings can be multiplied many times over when eco-routing services become available for consumers and other fleet owners (e.g., public transportation). The ubiquity of mobile phones presents an incredible opportunity for gathering information about all aspects of our world and the people living in it [17]. Already research has shown the potential for mobile phones with built-in motion detectors carried by everyday users to detect earthquakes mere seconds after they begin [12]. Navigation companies (e.g., waze, waze.com) increasingly use mobile phone records to estimate traffic levels on busy highways. There is a growing need for a cyber-infrastructure (e.g., Earth Cube initiative from NSF (www.nsf.gov/geo/earthcube/)) to facilitate our understanding of the Earth as a complex system. Technological advances have greatly facilitated the collection of data (from the field or laboratory) and the simulation of Earth systems. This has resulted in exponential growth of geosciences data and the dramatic increase in our ability to accommodate diverse phenomena in models of Earth systems. Such advances may be crucial for understanding our changing planet and its physics (e.g., ocean, atmosphere and land), biology (e.g., plants animals, ecology) and sociology (e.g., sustainable economic development, human geography) etc.

Work in spatial computing has been extensive over the past decades, particularly in the geographic context. It is hard to convey the breadth and depth of this large interdisciplinary body of work to the broad computing community in a short article. The goal of this article is twofold: (a) to share a broad perspective on spatial computing based on the discussions at the 2012 Computing Community Consortium (CCC) workshop (cra.org/ccc/visioning/visioning-activities/spatial-computing) and, (b) to start a discussion about the role the larger computing community can play in this interdisciplinary area. We do this by describing a few examples discussed at the workshop in sections 2, 4, and 5 without trying to either prioritize or be comprehensive (more examples appear in the Appendix). Finally, in Section 6, we advocate support for the broad interdisciplinary field beyond the examples presented in earlier sections. The article includes a few pictures to illustrate societal stories and visions discussed at the CCC workshop.

2 Transformative Accomplishments

Spatial computing initially arose to support computational representation and analysis of maps and other geographic data. Its influence was concentrated in highly specialized disciplines (represented by the professional organizations listed in Table 1). Since then, a number of transformative spatial computing technologies have become deeply integrated into society at large. These technologies help answer many kinds of questions humans have always asked. Here we briefly describe a few applications and research results of high significance and broad interest. Readers interested in a deeper exploration of spatial computing are encouraged to consult textbooks [6, 7, 38, 41, 5], monographs [36, 39] and encyclopedias [15, 40].

Geographic Information System (GIS): "Which countries are reachable by North Korea's missiles?" Figure 1 is a well known example of erroneous distance information computed on a planar map using circular distance, an easy mistake without the help of GIS supporting spherical measurements. GIS can understand a large number of map projections used by common geographic data producers and aid in fusing map data from diverse sources. As the Earth is not a perfect sphere, GIS also understands more accurate representations of the Earth, such as ellipsoid representations and non-parametric representations that use land-based geodetic reference points for localization. GIS captures, stores, analyzes, manages, and visualizes spatial data [21, 40]. It has a number of unique capabilities such as map projections, cartography, geodetic data, and map layers. For example, a map of the Earth is a representation of a curved surface on a plane. While map projections largely retain topological properties (except at map boundaries), retention of metric properties (e.g., distance, area) depends on the projection used. GIS can also join tables based on geometry to support spatial querying and statistical analysis, as detailed in the next two paragraphs. GIS has greatly benefited from computing advances such as algorithms (e.g., plane-sweep) and data-structures (e.g., triangulated irregular networks) related to map rendering, map overlay etc.



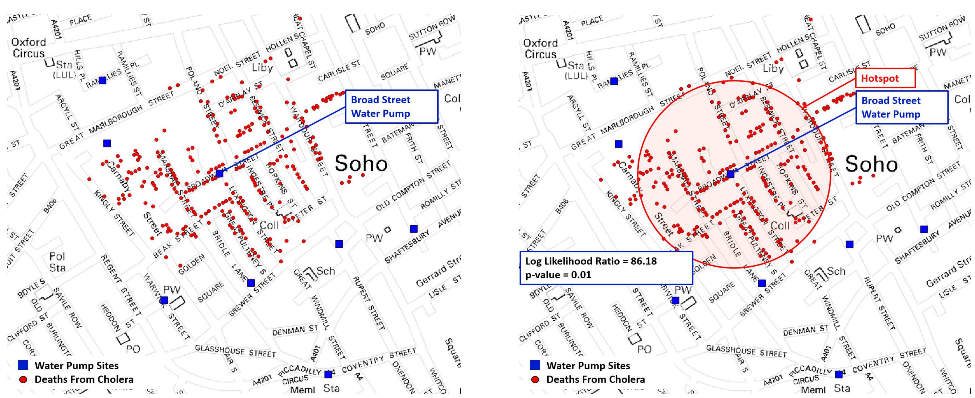
(a) Flat Earth

(b) Spherical Earth

Figure 1: Geographic Information System: A 2003 article in the Economist significantly underestimated the distance that North Korean missiles could travel because its map did not account for the spherical shape of the world. The correct version is shown on the right [10].

Spatial Database Management System (SDBMS): "Within the Sloan Digital Sky Survey, find galaxy pairs which are within 30 arc-seconds of each other." "Which houses are most likely to be flooded by global-warming-induced sea level rise or cloud burst or spring snow melt?" Before the development of spatial databases, these types of spatial queries required extensive programming and suffered from long computation times, due to the mismatch between 2-dimensional spatial data and the 1-dimensional datatypes (e.g., number) and indexes used by traditional database systems (e.g., B+Tree). In addition, a naive collection of spatial data types is inadequate for multi-stage queries since the result of some queries (e.g., union of disjoint polygons) cannot naturally be represented as a point, line, or polygon. Spatial Databases [41], such as Oracle Spatial and PostGIS, introduced spatial data types (e.g., OGIS simple features [33]), operations (e.g., inside, distance, etc.), spatial data structures (e.g., R-trees, voronoi diagrams), and algorithms (e.g., shortest-path, nearest neighbor, range query) to represent and efficiently answer multi-stage concurrent spatial queries. The reduced programming effort resulted in more compact code and faster response times.

Spatial Statistics: "Which areas of a silicon wafer have an unusually high concentration of defects?" "Has there been an outbreak of disease? Where?" In 1854, Dr. John Snow manually plotted Cholera locations on a street map of London to visually identify the outbreak hotspot around the Broad Street water pump (Figure 2(a)). It took several days to perform this analysis even for one disease over a small geographic area. Today, disease surveillance organizations monitor scores of infectious diseases over very large geographic areas using spatial statistical tests (Figure 2(b)) for detecting outbreaks (e.g., scan statistics) and hotspots as well as distinguishing these events from natural variations. Spatial Statistical techniques are also routinely used in public safety (e.g., hotspots of crime reports), very large scale integrated (VLSI) circuit design (e.g., defect hotspots on silicon wafers), weather forecasting (e.g., data assimilation), transportation (e.g., hotspots of accidents), mining (e.g., Kriging), public health (e.g., cancer cluster detection), agriculture (e.g., designing management zones for precision agriculture and sample design for agriculture census) etc. Spatial statistical theories (e.g., point processes, spatial auto-correlation, geo-statistics) address unique challenges (e.g., violation of independent identical distribution assumption) in applying traditional statistical models (e.g., linear regression, pearson correlation coefficient) to geographic data. Although spatial statistical techniques are an order of magnitude more computation-and-data intensive than traditional statistical techniques, the increased availability of inexpensive high performance computing and data technologies (e.g., sensors, SDBMS, GIS) in recent decades has facilitated wider interest in and adoption of spatial statistical methods [13].



(a) Location of pump sites and deaths

(b) Output of spatial statistical test

Figure 2: Analysis of water pump sites and deaths from cholera in 1854 [43].

Global Positioning System (GPS): "Where am I on the surface of the Earth?" "Where am I?" In the eighteenth century, "the longitude problem" [44] was among the hardest scientific problems. Lacking the ability to measure their longitude, sailors throughout the great ages of exploration had been literally lost at sea as soon as land was out of sight. Eventually with the combined help of compasses, maps, star positions, and the invention of the chronometer (a clock that worked on moving ships), it became possible to position oneself with some level of precision even in the middle of the ocean with no landmarks. With the 1978 launch of the Global Positioning System and its subsequent opening for civilian use, it is now possible to quickly and precisely locate oneself anywhere on the surface of the Earth. The Global Positioning System (GPS) is an example of a space-based global satellite navigation system (GNSS) [29] that provides location and time information anywhere on Earth where there is an unobstructed line of sight to four or more navigation satellites (out of a few dozen) [34]. GNSS'

Table 2: Recent Change in Spatial Computing

Late 20^{th} Century	21^{st} Century and Beyond
Sophisticated groups (e.g., Department of Defense, oil exploration) used GIS technologies	Billions use location-based services and update actual maps
Highly trained people in government agencies and surveying companies produce maps	Billions are mapmakers and many phenomena are observable
Only specialized software (e.g., ArcGIS, Oracle Spatial) could edit or analyze geographic information	More and more platforms are becoming location aware
User expectations were modest (e.g., assist in producing and distributing paper maps and their electronic counterparts)	User expectations are rising due to vast potential and risks

accurate timekeeping facilitates everyday activities such as clock synchronization in computer networks (e.g., Internet), geographic distributed sensor grids to monitor moving objects (e.g., missiles, planes, vehicles), electric power distribution grids, etc. Its localization capabilities have made possible a number of location-based services (LBS) for end users, such as turn-by-turn navigation, local search, and geo-coding. GNSS and LBS have become widely deployed and useful tools for commerce, science, tracking, and surveillance. Wide spread proliferation of GPS systems was made possible by its low cost VLSI implementations which could easily be integrated into mobile phones and tablets.

Remote Sensing [5]: "What fraction of the terrestrial surface is covered by forest?" "How has the forest cover changed over recent decades in the face of climate change, urbanization and population growth?" Traditionally, this question was answered using manual land surveys, which were labor intensive and limited to small areas. Modern remote sensing satellites (e.g., MODIS modis-land.gsfc.nasa.gov and Landsat landsat.usgs.gov) have made it possible to monitor land cover changes continuously on a global scale. In addition, specialized instruments can sense sub-surface resources such as aquifers, underground ocean on Jupiter's largest moon, etc. Due to the large data volume, computing technologies are crucial in storing, querying and analyzing remote sensing datasets. These datasets have also inspired computing innovations such as Google Earth.

3 Recent Change

In the late 20th century, most maps were produced by a small group of highly trained people in government agencies and surveying companies. Organizations such as the Department of Defense and oil exploration companies used highly specialized software such as ESRI ArcGIS and Oracle Spatial for editing or analyzing geographic information. As summarized in Table 2, recent advances in spatial computing have changed this situation dramatically. Today, users with cellphones and access to the internet number in the billions, meaning that virtually the entire planet now uses spatial technologies. The very success of spatial technologies has raised users' expectations of spatial computing in the future. At the same time, users increasingly worry about the potential misuse of location data.

Billions use location-based services and update actual maps: The proliferation of web-based technologies, cell-phones, consumer GPS-devices, and location-based social media has facilitated the widespread use of location-based services [39]. Internet services such as Google Earth and OpenStreetMap have brought GIS to the masses. With cell-phones and consumer GPS-devices, services such as Enhanced-911 (E-911) and navigation applications are consumed by billions of individuals. Facebook check-in and other location-based social media are also used by over a billion people around the world.

Billions are mapmakers and many phenomena are observable: Increasingly, the sources of geo-data are smart-phone users who may passively or actively contribute geographic information. The immediate effect is wider coverage and an increased number of surveyors for

Figure 3: Augmented reality applications are becoming commonplace for smartphones.

all sorts of spatial data. More phenomena are becoming observable because sensors are getting richer for 3D mapping, and broader spectrums at finer resolutions are being captured.

Multiple platforms are location aware: Traditionally, spatial computing support was limited to application software layers (e.g., ArcGIS), web services (e.g., Google Maps, MapQuest), and database management (e.g., SQL3/OGIS). In recent years, spatial computing support is emerging at several levels of the computing stack, including HTML 5, social media check-ins, Internet Protocol Version 6 (IPv6), and open location services (OpenLS).

Rising expectations due to vast potential and risks: Location-based services, navigation aids, and interactive maps have arguably exceeded users' expectations. Their intuitive basis and ease of use have earned these products a solid reputation. Consumers see the potential of spatial computing to reduce greenhouse gas emissions, strengthen cyber-security, improve consumer confidence and otherwise address many other societal problems. However, the very success of spatial computing technologies also raises red flags among users. Geo-privacy concerns will need to be addressed to avoid spooking citizens, exposing economic entities to liability, and lowering public trust.

4 Short-Term Opportunities

The profound changes outlined above provide emerging avenues of research in spatial computing and give rise to a number of new and exciting opportunities:

Augmented Reality Systems: Augmented reality enriches our perception of the real world by overlaying spatially aligned media in real time. For example, it can alter a user's view of their environment by adding computer graphics to convey past, present or future information about a place or object, as shown in Figures 3 and 4. It is already used in heads-up displays in aircraft and has become a popular feature in smartphone applications. As lightweight, but powerful, computer-driven eyewear becomes more commonplace, augmented reality will play a crucial role in fields such as medicine, architecture, tourism and commerce, engineering, civil/urban planning, assembly and maintenance, as well as in general day–to–day intelligence amplification. New spatial computing research challenges in this area stem from the need for new algorithms as well as cooperation between users and the cloud for full 3D position and orientation pose estimation of people and devices and registration of physical and virtual things. What are natural interfaces leveraging all human senses (e.g., vision, hearing, touch, etc.) and

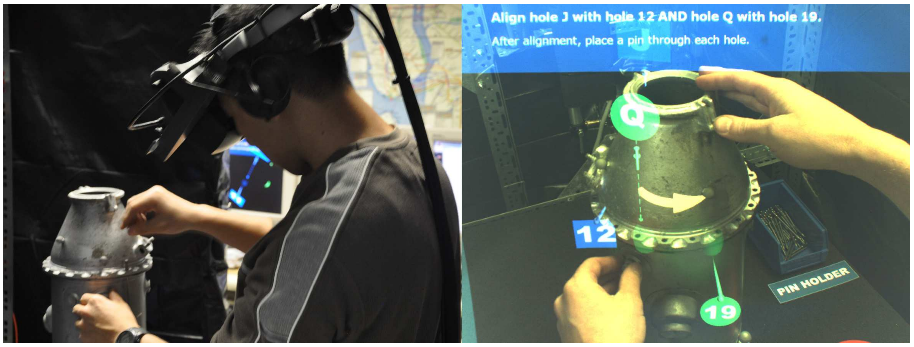


Figure 4: Experimental augmented reality assistance for an aircraft engine assembly task.

controls (e.g., thumbs, fingers, hands, legs, eyes, head, and torso) to interact with augmented reality across different tasks? How can we capture human bodies with their full degrees of freedom and represent them in virtual space?

Spatial Predictive Analytics: Recent progress in spatial statistics [36] and spatial data mining [42] has the potential to improve the accuracy and timeliness of predictions about the future path of hurricanes, spread of infectious diseases, and traffic congestion. Such questions have confounded classical prediction methods due to challenges such as spatial auto-correlation, non-stationarity, and edge effects. Spatial models can be invaluable when making spatio-temporal predictions about a broad range of issues, including the location of probable tumor growth in a human body or the spread of cracks in aircraft wings or highway bridges. Questions that need to be answered in this research area include: How may machine-learning techniques be generalized to address spatio-temporal challenges of auto-correlation, non-stationarity, heterogeneity, multi-scale, etc.? How can frequent spatio-temporal patterns be mined despite transaction-induced distortions (e.g., either loss or double-counting of neighborhood relationships)? What are scalable and numerically robust methods for computing the determinants of very large sparse (but not banded) matrices in the context of maximum likelihood parameter estimation for spatial auto-regression modeling?

Geo-collaborative Systems, Fleets and Crowds: Spatial computing promises to take the Internet beyond cyberspace, enabling connections among fixed structures and moving objects such as cars, pedestrians, and bicycles, to help prevent collisions or coordinate movement in smarter cities. For example, the city of Los Angeles recently interconnected all of its 4,500 traffic signals to improve traffic flow during rush hour. Spatial computing enables smart-mobs (groups of people) to come together quickly for common causes, reducing the need for any one person to lead. For example, drivers, smart cars, and infrastructure may cooperate in the future to reduce congestion, speed up evacuation, and enhance safety. This raises the challenge of "trust" while using a group of spatial agents for computation and decision making: How may geographically distributed agents (e.g., smart signals and cars) cooperate in a trustworthy manner (e.g. despite GPS spoofing)?

Moving Spatial Computing Indoors and Underground: Despite worldwide availability, GPS signals are largely unavailable indoors, where human beings spend 80% to 90% of their time [28]. Location-based services, such as route navigation, currently fill 10% to 20% of our time but, with emerging technologies such as indoor localization, routing, and navigation (already available in major airports and hospitals), the new expectation in the 21st century is that our spatial context will be available essentially all the time, leveraging localization indoors and underground (e.g., mines, tunnels) via cell-phone towers, Wi-Fi transmitters, and other indoor infrastructure. Indoor localization raises several new research questions such as: What scalable algorithms can create navigable maps for indoor space from CAD drawings? What about buildings without CAD drawings? How can we perform reliable localization in indoor spaces where GPS signals are usually attenuated?

5 Long-Term Research Needs

Spatial computing is no doubt providing society with tremendous value, but out of these successes, significant challenges are emerging. Meeting these challenges will require expertise beyond the realm of spatial computing itself. First, overcoming the challenges of the public being mapmakers and most phenomena being observable will require moving from the fusion of data from a few trusted sources to the synergizing of data across a multitude of volunteers. Second, surmounting the challenge of equipping several platforms to be location-aware will move spatial computing from a few platforms (e.g., cellphones) to almost all platforms (e.g., sensors, PCs, clouds). Third, understanding of human cognition is needed to ensure all members of society benefit from location-based services. Finally, spatial computing will need to settle once and for all users' trust and worries about privacy.

From Fusion to Synergetics: Historically, popular GIS software products (e.g. ESRI Arc family, PCI Geomatica, and ERDAS IMAGINE) were designed for geometric data (e.g., point, lines and polygons) and raster data (e.g., satellite imagery). Today, an ever-increasing volume of geographic data is coming from volunteer citizens via check-ins, tweets, geo-tags, geo-reports from Ushahidi, and donated GPS tracks. Volunteered geographic information (VGI) raises challenges related to data error, trustworthiness, bias, etc. The political and legal consequences of errors in spatial computing technology may be high. For example, after Hurricane Katrina, there was considerable concern in Congress about the fact that the delays in releasing federal maps of New Orleans' most flood-prone neighborhoods had slowed rebuilding and created uncertainty [19]. Such political/legal complications may worsen in the future. Addressing these challenges requires a shift from traditional data fusion ideas to a broader paradigm of data synergetics, raising in turn many new issues. For example, volunteers often use place-names (e.g., silicon valley) and prepositions (e.g., near, in, at, along, etc.) instead of numerical coordinates (e.g., latitude-longitude). We need methods for porting the current numerical-coordinate based data-structures and algorithms to spatial data with place-names and spatial prepositions. In addition, spatial and spatio-temporal computing standards are needed to more effectively utilize VGI via quality improvement processes (e.g., peer review, testing for recency) and documentation of quality measures (e.g., positional accuracy).

From Sensors to Clouds: In the 20th century, the public face of spatial computing was represented by software such as ArcGIS and Oracle Spatial Databases. Today, all levels of the computing stack in spatial systems are being influenced by the fact that ever more platforms are location-aware due to the widespread use of smart-phones and web-based virtual globes. New infrastructure will be needed to support spatial computing at lower layers of the computing stack so that spatial data types and operations may be appropriately allocated across hardware, assembly languages, operating system kernels, runtime systems, network stacks, database management systems, geographic information systems, and application programs. Augmented reality capabilities will be needed to accommodate devices such as eyeglass displays and smart-phones for automated, accurate, and scalable retrieval, recognition, and presentation of information. Sensing opportunities exist for providing pervasive infrastructure for real-time centimeter-scale localization for emergency response, health management, and real-time situation awareness for water and energy distribution. Computational issues [6] raised by Spatial Big Data will create new research opportunities for cloud computing by addressing the size, variety, and update rate of spatial datasets that currently exceed the capacity of commonly used spatial computing technologies to learn, manage, and process data with reasonable effort.

Spatial Cognition First: Previously, spatial computing services were defined for a small number of GIS-trained professionals who shared a specialized technical language not understood easily by the general public. With everyday citizens using location-based services and becoming mapmakers themselves, there is an urgent need to understand the psychology of spatial cognition. Such understanding will improve the use and design of maps and other geographic information products by a large fraction of society. Further research on spatial cognitive assistance is needed to explore ideas such as landmark-based routing for individuals who cannot read maps or for navigating inside a new space such as a building or campus where not all areas (e.g., walkways) are named. Understanding group behavior in terms of participative planning (e.g., collaboration on landscape, bridge, or building design) or smart mobs for coordinating location movement will enhance spatial computing services for groups of people, as opposed to individuals. Context (e.g., who is tweeting, where they are, and physical features in the situation) should also be brought into these scenarios to investigate new opportunities for tweet interpretation for warning alerts during emergencies such as natural disasters (e.g., Hurricane Sandy). New ways of understanding our spatial abilities (e.g., navigation, learning spatial layouts, and reading maps) and the way different groups (e.g., drivers and pedestrians) think about space must be further investigated to leverage some of these opportunities: How do humans represent and learn cognitive maps? How may spatial cognition concepts improve usability of spatial computing services? How can we create user interfaces that bridge the gap between spatial computing "in the small" (typically on indoor desktop systems with stereo displays and precise 3D tracking) and spatial computing "in the large" (typically outdoors using coarse GNSS on mobile/wearable devices)?

Geo-Privacy: Finally, while location information (e.g., GPS in phones and cars) can provide great value to emergency response personnel, consumers, and industry, streams of such data also introduce serious privacy and trustworthiness questions related to the use of geo-location and geo-surveillance to monitor and control citizens (a.k.a. stalking, geo-slavery [8] and geo-privacy [18, 31, 1, 35]). For example, Google Street View (www.google.com/maps/ views/streetview) was accused of privacy violations and suffered temporary bans in multiple countries. Striking a balance between utility and privacy remains a difficult challenge. Computer science efforts at obfuscating location information to date have largely yielded negative results. Thus, many individuals hesitate to indulge in mobile commerce due to concern about privacy of their locations, trajectories and other spatio-temporal personal information [18]. Computer scientists will need to join forces with policy makers and other advocates to ensure consumer confidence in the future. New legal principles need to be designed that align with Fair Information Practices [1], especially those related to notice, transparency, consent, integrity and accountability. However, this raises a number of questions: What would be considered as an "adequate notice" for spatial data being collected? How to seek proper consent? What and how long should information be stored? More broadly: When does localization (e.g., GPS-tracking) lead to privacy violation? Is reducing spatio-temporal resolution sufficient to discourage stalking and other forms of geo-slavery? How do we serve the needs of society (e.g., tracking infectious disease) while protecting the privacy of individuals?

6 Final Considerations

Spatial computing promises an astounding array of opportunities for researchers and entrepreneurs alike during the coming decade. Successfully harnessing the potential will require significant investment and funding of spatial computing research topics including but not limited to the examples listed earlier. Currently, many spatial computing projects are too small to achieve the critical mass needed for major steps forward. Benefactors need to strongly consider funding larger and more adventurous efforts involving a dozen or more faculty groups across multiple universities. Some exemplary initiatives include the US National Center of Geographic Information and Analysis (NCGIA), GEOmatics for Informed Decisions (GEOIDE) network in Canada, RGE in Netherlands, the Cooperative Research Centre for Spatial Information (CRCSI) in Australia. Another barrier for progress in research has been the fact that grant proposals are often reviewed by panels with few or no spatial computing experts, sometimes resulting in a lack of champions. Funding agencies should consider ways to address this issue using special review panels and specialized requests for proposals.

A number of agencies have research initiatives in spatial computing [23, 25, 26, 24, 22] (e.g., the National Cancer Institute's Spatial Uncertainty: Data, Modeling, and Communication; the National Geospatial-Intelligence Agency's Academic Research Program; and the Chorochronos project [16] funded by the EU). Given its cross cutting reach, benefactors can establish computer science leadership in this emerging area of critical importance by creating a dedicated and enduring research program for spatial computing. Multi-agency coordination to reduce competing projects and facilitate interdisciplinary and inter-agency research would benefit the entire field as well as the agencies themselves.

Finally, spatial computing scientists need more institutional support on their home campuses. Beyond one-time large grants, it will be necessary to institutionalize spatial computing research programs. A few research universities have established GIS centers (akin to computer centers of the 1960s) as well as campus wide spatial initiatives (e.g., spatial@UCSB and U-Spatial at University of Minnesota) which serve research endeavors across a broad range of disciplines including climate change and public health. More research universities need to follow their lead.

Spatial computing has already proven itself as a major economic opportunity to society and further support for spatial computing research can ensure even more revolutionary advances to come.

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A Representative Computer Science Questions in Spatial Computing

Sub-Area	Representative Questions
Collaborative Systems	How can computation overcome geographic constraints such as transportation cost, language and cultural variation across locations?
Data - Database	How may we reduce the semantic gap between spatio-temporal computations and primitives (e.g., ontology, taxonomies, abstract data-types) provided by current computing systems? How do we store, access, and transform spatio-temporal concepts, facilitating data sharing, data transfer, and data archiving, while ensuring minimum information loss? How do we fuse disparate spatial data sources to understand geographic phenomena or detect an event, when it is not possible via study of a single data source?
Data - Data Analytics	How may machine learning techniques be generalized to address spatio-temporal challenges of auto-correlation, non-stationarity, heterogeneity, multi-scale, etc.? How can we elevate data analytics above current engineering practices to incorporate scientific rigor (e.g., reproducibility, objectiveness)? How can spatio-temporal data be analyzed without compromising privacy? How can frequent spatio-temporal patterns be mined despite transaction-induced distortions (e.g., either loss or double-counting of neighborhood relationships)? How can data analytic models be generalized for spatio-temporal network data (e.g., crime reports in cities) to identify patterns of urban life? What can be mined from geo-social media logs, e.g., check-ins, mobile device trajectories, etc.? How may one estimate evacuee population? Traffic speed and congestion? Urban patterns of life?
Hardware	Which spatio-temporal computations are hard to speed up with GPUs? multicore? map-reduce? Which benefit? How may one determine location of a person (or device) despite challenges of motion, GPS-signal jamming, GPS-signal unavailability indoor, etc.? How may geo-localization of IP-addresses be improved by tighter integration of Internet and GPS infrastructure?
Human Computer Interaction	How can user interfaces exploit the new generation of miniature depth cameras that will be integrated with mobile and wearable devices? What kinds of interaction tasks can be performed more efficiently and more accurately with these systems? How can ubiquitous interactive room-scale scanning and tracking systems change the way in which we interact with computers and each other? How can we create user interfaces that bridge the gap between spatial computing "in the small" (typically on indoor desktop systems with stereo displays and precise 3D tracking) and spatial computing "in the large" (typically outdoors using coarse GNSS on mobile/wearable devices)?
Networks	How may one determine, authenticate and guarantee the location of an Internet entity (e.g., client, server, packet) despite autonomy, heterogeneity, transparency, etc?
Security and Privacy	How may one authenticate location of a person or device despite the challenges of motion, location-spoofing, physical trojan-horses, etc.? Does GPS-tracking violate privacy? What is the relationship between the resolution of spatio-temporal data and privacy? How do we quantify privacy of spatio-temporal data? What computational methods can enhance the privacy of spatio-temporal data?
Software	For the best balance between performance and flexibility, what it the appropriate allocation of spatial data-types and operations across hardware, assembly language, OS kernel, run-time systems, network stack, database management systems, geographic information systems and application programs?
Spatial Cognition	How can spatial thinking enhance participation in STEM fields? How do humans represent and learn cognitive maps? What is impact of GPS devices on human learning? What is the SC impact of changing to a mobile ego-centric frame of reference from an earth-centric frame such as latitude, longitude, and altitude?
Spatial Reasoning and Artificial Intelligence	What are components of spatial intelligence? Can computers have as much spatial intelligence as humans? How can computational agents reason about spatio-temporal concepts (e.g., moving objects, lagrangian frame of reference, constraints and relationships)?

Theory - Algorithm Design, Numerical Analysis	Can we design new algorithm paradigms for spatio-temporal problems which violate the dynamic programming assumptions of stationary ranking of candidates? How can one design robust representations and algorithms for spatio-temporal computation to control the approximation errors resulting from discretization of continuous space and time? What are scalable and numerically robust methods for computing determinants of very large sparse (but not banded) matrices in context of maximum likelihood parameter estimation for spatial auto-regression mode?
Visualization, Graphics	How may one visualize spatio-temporal datasets with uncertainties in location, time and attributes? How can we automate map creation similar to attempts in the database field to automate database administration tasks (e.g., index building, etc)?

Table 3: Geo-concepts pushing new computer science

B Other Transformative Accomplishments

Location-based Services (LBS): "Which police car or ambulance is near a 911 caller using a smartphone?" When outside a building, it can be difficult for a caller to articulate their position, and for the dispatcher to identify a nearby police car or ambulance. These challenges result in slow response times for emergency services for mobile callers. With the advent of systems like E-911, a requirement where mobile phones would self-locate with GPS or ground-based localization infrastructure to automatically report location information to a 911 center, dispatching nearby police cars and ambulances to correct locations is faster and more accurate. This is an example of Location-based Services. Commercial use-cases of LBS include local search, proximity based advertising, location-based social networks, etc. The OpenLS standard, a technical specification for LBS, describes a set of core services including localization, directory service (geocoding, reverse geocoding), route determination. Efficient algorithms for analytics over spatial networks (e.g., nearest neighbor techniques and hierarchical routing for road networks [41, 40, 38]) have been one the most central pieces for a successful realization of Location-based services. These techniques help build large scale systems which can cater to the core services of a LBS.

Digital Earth: "What is the spatial distribution of a population of a city before and after an earthquake?" In the past, two challenges prevented fast and efficient response to this question. First, detailed spatial information (e.g., remotely sensed imagery, census data) did not have the broad access it has now through the advent of Virtual Globes (e.g., Google Earth, NASA World Wind, Microsoft Bing Maps). Second, surveying population location and movement was a time consuming and expensive procedure. With today's Volunteered Geographic Information services such as Ushahidi [30] and Open Street Maps (OSM), everyday citizens can create maps, submit information, and aid in overall relief efforts. For example, after the Haiti earthquake disaster, people across the world used OSM to digitize post-earthquake areal-imagery to quickly update maps of Haiti's roads and hospitals that were still functioning and the locations of triage centers and refugee camps [27]. These collections of tools enable and extend Al Gore's vision of a "Digital Earth," where citizens will not only "access vast amounts of scientific and cultural information to help them understand the Earth and its human activities," but also contribute new information themselves [3]. Development of SDBMS, large capacity (terabyte size) storage devices, multi-resolution map rendering algorithms were the key computational techniques behind this revolution.

C Other Short-term Opportunities

Spatial Abilities Predict STEM Success [46]: Spatial abilities include navigation, learning spatial layouts, and performing mental rotation, transformation, scaling and deformation of objects across space-time. Recent evidence [46] suggests that spatial skills influence who will go into and succeed in the fields of science, technology, engineering, and math (STEM). As it stands, our society is facing a challenge in educating and developing enough citizens who can perform jobs that demand skills in STEM domains. Improving spatial training at K-12 levels is likely to increase the number of students who excel in and pursue careers in STEM fields. Questions that need to be pondered in this area include: How do we improve STEM learning and spatial thinking using spatial computing? How may spatial computing be designed to further strengthen spatial abilities of interest to STEM disciplines?

Harnessing emerging Spatial Big Data: Emerging spatial big data include trajectories of cell-phones and GPS devices (shown in Figure 5), mobile check-in's, wide-area motion imagery, and location-based search information. Spatial big data has the potential of providing new understanding and spurring innovation. A 2011 McKinsey Global Institute report estimated savings of $600 billion annually by 2020 through reductions in vehicle idling and fuel use via smarter navigation [20]. Location information from cellphones will allow urban informatics, allowing for real-time census information to be gathered for public health, safety and prosperity. Spatial Big Data spurs several new opportunities for computer science research: Can SBD be used to remove traditional issues with spatial computing, such as the common problem of users specifying neighborhood relationships (e.g., adjacency matrix in spatial statistics) by developing SBD-driven estimation procedures? How might we take advantage of SBD to enable spatial models to better model geographic heterogeneity, e.g., via spatial ensembles of localized models?

Time-Travel and Depth in Virtual Globes: Virtual globes such as Google Earth, Bing Maps, and NASA World Wind are being used to understand our changing planet in an intuitive manner. Time-travel and depth (e.g., subsurface, atmosphere) in virtual globes will provide the ability to visualize historical and future scenarios on a global scale for use cases such as visualizing change in ocean currents, atmospheric wind flows and arctic ice-sheet over recent decades, as well as climate projections under alternative policy scenarios. However, in order to support all of these tasks, it will first be necessary to develop representations that capture both the data and any associated metadata about multiple views of past, present, and future. How can we incorporate provenance, accuracy, recency, and the semantics of the data? Given a rich representation of the data with diverse views, what new techniques are needed to exploit all of this metadata to integrate and reason about the diverse available sources?

Persistent Large Area Environmental Monitoring: Environmental influences on the air we breathe, the water we drink, or the food we eat, are known to impact health and safety [4, 32]. Spatial computing (e.g., through VGI and location-aware sensor networks) can greatly enhance spatio-temporal precision and accuracy of exposure data in

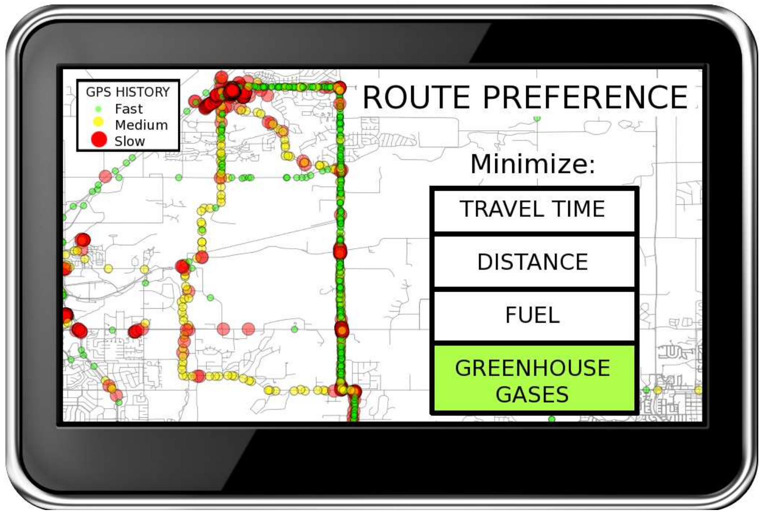

Figure 5: GPS trace data can be used to highlight delays and slowdowns in driving, suggesting more efficient routes.

sensitive environments such as schools, hospitals, fragile eco-systems, vulnerable public gathering places, in addition to many other applications. Such exposure data can be analyzed for better decision support, planning and emergency preparedness. One of the key challenges in realizing efficient monitoring of large geographic areas is effective use of limited bandwidth between the sensors and the central computational infrastructure. What is the optimal division of analysis between computing at the sensor level–which is locally available but limited in computing power (e.g. smart-phone processor)–and remote data center based computing–which is more powerful but require communication bandwidth?

Localizing Cyber Entities: Location is fast becoming an essential part of Internet services, with HTML 5 and IPv6 providing native support for locating browsers and GPS-enabled phones locating people on the move. Location authentication on the Internet may enhance cyber-security by helping verify the identity and location of message sources. For example, geo-targeted warnings for people in predicted tornado paths can help save lives by reducing false warnings. Societal adoption will require trust in such systems against threats related to security, privacy, confidentiality, etc. Localizing cyber entities poses significant challenges for geo-coding techniques. Can the current techniques, which are limited to textual information, can scale up to handle images and videos over internet? How may we geo-locate cyber entities such as images and videos?

3D Mapping and Visualization: Current and emerging mapping and GIS technologies are being used to garner new knowledge about the Earth and understand the world we live in. For example, technologies such as Google Street View (www.google.com/maps/views/streetview) provide panoramic views from positions along many popular streets (e.g., downtowns) and trails (e.g., Grand Canyon) in the world. Shops, cafes, restaurants, and other retail businesses may choose to display panoramic images of the interior of their premises which are then included in Street View (e.g., Google Street View). The benefits of 3D mapping to society are already evident in that park-

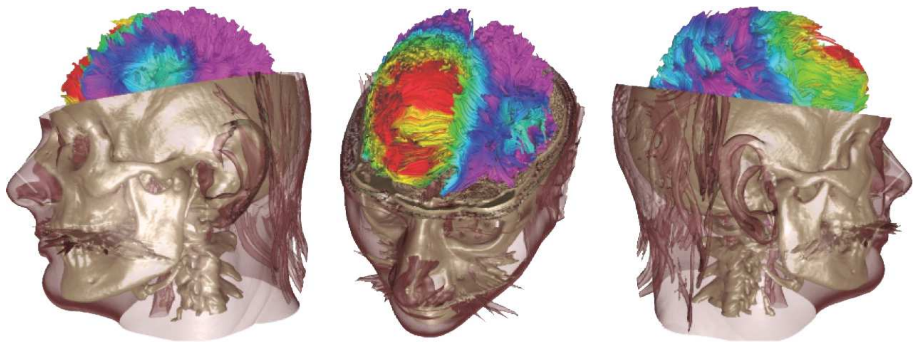

Figure 6: An example of non-geographic space. Spatial computing ideas can transform information management in non-geographic spaces, such as the brain. Neuro-maps may organize patient data (e.g., MRI, CT). Figure courtesy of Technische Universität München/ KAUST/University of Utah/University of Konstanz/DFKI Saarbrücken.

ing, left turn lanes, and one-way streets can be viewed before traveling. Technologies such as GigaPan (gigapan.com) also provide detailed panoramas, which may be leveraged for virtual tours of points of interest (e.g., UNESCO world heritage sites (whc.unesco.org/en/about/)).

Beyond Geographic Space: Spatial computing ideas can also transform information management in non-geographic spaces (Table 4). For example, defect locations on silicon wafers may be modeled as statistical point processes to identify hotspots. Neuro-maps (shown in Figure 6) may organize patient data (e.g., MRI, CT) and intra-human body position tracking may facilitate navigation along a least-invasive route to reach and remove brain tumors. Astro-maps chart the stars and interplanetary localization systems may improve space travel, whereas knowledge-maps plot our ideas and thoughts. These domains may benefit from the rich conceptualization of geographic space developed over centuries. Non-geographic spaces raise some fundamental questions for spatial computing. For example, what reference coordinate systems (e.g., latitude-longitudes for Earth) are most suitable for queries in non-geographic spaces? Inside the human body, for instance, we may use rigid structures (e.g., skull and bones) for reference but, we would also have to accommodate the variation in these structures across humans. What is the computational structure of routing problems (e.g. least invasive path to a brain tumor that minimizes tissue damage) in a non-geographic space such as the human body?

Table 4: Representative spaces of interest in spatial computing

Outer Space	Moon, Mars, Venus, Sun, Exoplanets, Stars, Milky Way, Galaxies
Geographic	Terrain, Transportation, Ocean, Mining
Indoors	Inside Buildings, Malls, Airports, Stadiums
Human Body	Arteries/Veins, Brain, Genome Mapping, Chromosomes, Neuromapping
Micro / Nano	Silicon Wafers, Materials Science

D Platform Trends

The main platform trends in spatial computing stem from Graphics & Vision, Interaction Devices, LiDAR, GPS Modernization, Cell Phones, Indoor Localization, Internet Localization, and Cloud Computing. These platform trends are summarized next.

Graphics and Vision Increases in the scale and detail of virtual models are driven by the desire for worlds that are more complete, detailed, varying, and realistic. Significant advances in graphics hardware will make it feasible to deal with much larger scales. For larger scale and more detailed models, representation, creation, and usage must be considered. Representation needs to be considered because all details cannot be stored for highly detailed models. Creation is important because precise manual descriptions of virtual models are not possible. Usage is critical because processing with new models is non-trivial and things are possible that were not possible before.

Interaction Devices The democratization of technology has lead to ubiquitous computation and sensing. Commonly available interaction devices include smartphones (with multi-core CPU, GPU, Wi-Fi, 4G, GNSS, accelerometers, gyros, compass, cameras), game controllers (with Accelerometers, gyros, compass, cameras, depth cameras, electromagnetic trackers), and desktop peripherals (e.g., cameras). New challenges arise in bridging the gap between geospatial and 3D user interfaces (e.g., large to small, outdoors to indoors, coarse to fine, position/orientation to full body pose, Hz to kHz). A key trend here is the proliferation of depth camera systems. These first entered consumer devices through game console peripherals designed to sense users a few meters away from the display (Kinect for Xbox). However, there is now a new generation of inexpensive camera-based depth tracking systems for desktop applications that work in the sub-meter and even sub-foot range: Microsoft Kinect for Windows, PrimeSense Carmine, PMD Technologies, SoftKinetic DepthSense, Creative Interactive Gesture Camera). These devices and their SDKs support interactive tracking of 3D full body pose (at a distance), head/hand/finger tracking (up close), and modeling of the environment when the device can be moved around (e.g., KinectFusion).

Localization Next generation localization includes image-based, indoor-based, and internet-based techniques. Due to the prevalence of mobile/handheld devices with numerous sensors (e.g., smart phones) and the recent advances in computer vision and recognition, image-based localization is an emerging trend for both indoor and outdoor localization. The idea is to take a query image with a mobile device equipped with sensors (e.g., gyros, GPS, accelerometers), build a geo-tagged image database (preferably 3D), retrieve the "best" match from the database, and recover the pose of the query image with respect to the retrieved image database. This has application in augmented reality and location-based advertising & services. For indoor localization, augmented reality has interesting challenges when dealing with a wide range of scales/resolutions and conditions. Examples of scale include finding a meeting room in a building, finding a paper in the room, finding an equation on the paper, determining which variable is the weighting in the equation, etc. Trends involve optimization for what matters and using all sources (e.g., large + detailed models, constraints, inferences, cloud, etc.). For internet-based localization, tremendous possibilities exist as we move to cm/dm real-time starting with networked differential GPS at sub-meter scales.

GPS Modernization With land area of approximately 1.5 x 108 km2, human population of about 7 billion people, number of cell phones at 5.6 billion (80% of the world), and number of seconds per year at 3.14 x 107, map making at human scales, particularly in developing countries, is a challenge. Interesting opportunities have arisen in geodetic support for disaster relief amid very little data, validation, crowd sourcing, and crowd mapping.

Mobile devices With the ubiquity of cellphones, interesting questions arise such as how may one overcome challenges of limited user attention, display, power, etc? How can one accurately determine location (and orientation) of mobile clients in GPS-denied spaces such as indoors and underground? What can be mined from geo-social media logs, e.g., check-ins, mobile device trajectories, etc?

Cloud Computing The advent of big spatio-temporal data has raised interesting challenges such as which spatio-temporal computations are hard to speed up with cloud computing and which benefit. New challenges in spatio-temporal graphs, streaming spatial data, load balancing, distributed query processing and data partitioning should be considered.