Mapping Traffic Pollution Exposure: the Quantified Self

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Summary: The purpose of this paper is to apply recent developments in the areas of the 'Quantified Self' and the 'Internet of Things' in order to explore the use of low-cost sensors for the collection of a variety of spatially-referenced biometric and environmental data from participants. This is achieved using a specially designed application on the Android mobile platform, which has been developed for this project in order to log serial sensor data via USB against GPS location and timestamp, allowing the spatio-temporal mapping of a variety of personal data. In this case, traffic pollution data is collected and compared with a measures of nasal airflow, permitting an estimate of exposure to traffic pollution for an individual on a given journey. These data will be fed back to individuals in order to assess the level of correlation with their reported perception of exposure to pollution, as well the extent to which this influences subsequent behaviour; such as whether or not an individual will modify their route for a given journey based upon their new knowledge of pollution levels. In this way, personal pollution exposure can be empirically monitored at the individual level, allowing for a more in-depth understanding of these issues than has so far been possible.

1. Introduction

1.1. Pollution Modelling

There is much evidence that traffic pollution has a number of health implications ranging from irritation to the eyes, nose and throat to nausea, respiratory problems and even death (Davies and Whyatt, 2014; Heinrich et al., 2005). An individual's exposure to pollution is typically greatest when travelling, and depends principally upon the duration of exposure, and volume of pollutants inhaled (Davies and Whyatt, 2014). In turn, these considerations are dependent upon a wide variety of factors including the physiology of the individual, climatic conditions and terrain. There has been a significant amount of research relating to the estimation of exposure to pollutants using a variety of modelling techniques (Davies and Whyatt, 2014; Gulliver and Briggs, 2005; Crabbe and Hamilton, 2000), but thus far there has been little evidence of attempts to directly sense pollution levels and physiological condition. This is likely to be a result of the expense and impracticality of doing so, as such monitoring equipment has, until recently, been bulky, power-hungry, and too expensive to operate at the individual level. One notable exception to this is the work of Int Panis et. al. (2010), who include respiratory measurements in their comparison of pollution exposure for car users and cyclists.

1.2. 'Quantified Self' and the 'Internet of Things'

McFredries (2013) describes the 'digital exhaust' that we generate with almost every action that we take in the modern world. Whether through paying for something with a credit card; answering an email; making a phone call; or posting to social media, data regarding our activities are increasingly logged online both intentionally and unintentionally. Those individuals who choose to record this data intentionally are described as 'self trackers', and they may create detailed records of their food, exercise and location, as well as a number of sensor-driven records relating to phenomena such as mood, alertness and wellbeing (McFredries 2013). At its most extreme, this activity is referred to as the "Quantified Self" (QS) (Wolf, in Bottles 2012), which has developed from a single blog in 2007 (Wolf, 2007), into a number of research-driven applications including automated stress recognition, nonverbal communication methodologies to support autistic children, and automated interventions for drug addicts (Bottles, 2012).

The 'Internet of Things' (IoT), on the other hand, refers to the paradigm whereby many of the everyday and existing objects around us are connected to the network, with the purpose of "*embedding intelligence into our environment*". The IoT 'vision' effectively represents an evolution of the current internet into a network of objects that harvest environmental information through sensing; whilst at the same time interacting with the physical world, providing the analysis and communication of these data (Gubbi et. al., 2014). Gubbi et. al. (2014) provide a detailed overview of the ‘vision’, history and likely future development of the IoT.

Swan (2012b) provides a relatively comprehensive review of the technologies involved in QS, and describes the increasing availability of low-cost sensors as one of the biggest drivers of both QS and the IoT. Swan (2012b) describes sensors for movement, sound, light, electrical potential, temperature, moisture, location, heart rate and Galvanic Skin Response (GSR) which may be utilised in any number of self-tracking applications. Swan (2012b) also contemplates the future of such sensor platforms, including wearable sensors such as Google Glass, and even ‘patch’ sensors: low-cost disposable ‘digital tattoos’ akin to nicotine patches that are worn for days to monitor attributes such as heart rate; temperature; brain activity or hydration level, and are then discarded. In recent years, this has even extended towards attempts to record emotions, driven by the increasing availability of consumer EEG’s (electroencephalography sensors), eye-tracking algorithms, and GSR sensors.

The use of these sensors has been widespread for a number of years now, but thus far research has been quite introverted, focussing upon the self and not yet fully engaging with subjects’ perceptions of their surrounding environment. Applications in the literature include, for example, patient monitoring (Worringham et al., 2011); emergency health monitoring (Ramalingam, 2012); preventative medicine (Swan, 2012); physical activity monitoring (Duncan, 2009; Fjørtoft, 2009; Fjørtoft, 2010; Castellano, 2010); and a number of consumer lifestyle and fitness applications (examples listed in Swan 2012b). Research accounting for perceptions of the environment, however, is largely limited to the simple, non-automated collection of geotagged data. One example of this is Whyatt et al. (2008), where children used mobile phones with on-board cameras and Bluetooth-paired GPS receivers to collect geotagged imagery and comments relating to their journeys to school.

1.3. Aims and Objectives

Continued developments in the IoT are driving the miniaturisation and cost-reduction of an ever-broadening range of sensors, making it increasingly possible to construct cheap low-power systems that are able to monitor environmental phenomena such as air pollution, water quality and wind speed. Used in combination with the existing QS sensors for a broad range of biometric and physiological measures, these technologies have the potential to facilitate research into the interaction between the individual and their surrounding environment in ways that have not previously been possible. The aim of this project, therefore, is to utilise these low-cost and small-size sensors in order to explore participants' perception of exposure to traffic pollution on a journey that they make regularly. Georeferenced data on levels of traffic pollutants and nasal air flow will be recorded using small sensors attached to an individual, in order that levels of pollution 'exposure' (i.e. amount of inhaled pollutants) may be calculated and used in order to produce a 'personal exposure map' for a given individual and journey. This sensor-based approach removes the requirement for models or assumptions relating either to local variations in the concentration of pollutants, or the physiology of an individual thus permitting a wholly empirical analysis into exposure to take place.

2. Methodology

This project will rely upon the collection of geotagged data relating to the concentration of carbon monoxide (CO), carbon dioxide (CO_2), nitrogen dioxide (NO_2), and the participant's nasal air-flow. All of these data will be recorded using a specially developed mobile application for the Android operating system, known as 'Spatial Logger'. This application logs a time-stamp and GPS-derived location (taken from on-board sensors) along with any data fed to the phone via a USB serial interface, at a given temporal resolution. In this case, airflow data will be collected using an Arduino 'Uno' board (http://arduino.cc/en/Main/arduinoBoardUno) with the Cooking Hacks 'e-Health' shield (http://www.cooking-hacks.com/documentation/tutorials/ehealth-biometric-sensor-platform-arduino-raspberry-pi-medical); and the pollution data will be collected using the Libelium Waspmote 'Gases Board' (http://www.libelium.com/products/waspmote/). These devices are shown in Figure 1.

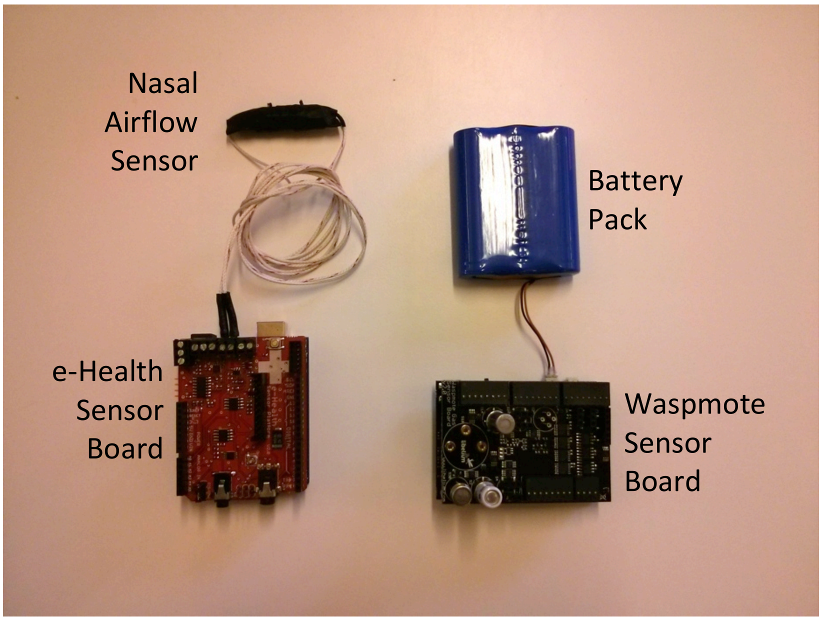

Figure 1. The Cooking Hacks e-Health sensor boards for airflow (left), and the Libelium Waspmote Gases sensor board for pollution (right).

Participants in this study will carry this system during a journey that they regularly make (for example their journey to work), as this is typically when an individual's pollution exposure is greatest (Davies and Whyatt, 2014). The Spatial Logger application will log time, position, airflow and pollution concentrations into a single CSV file, which can then be transferred to a computer for analysis either wirelessly or via USB cable. The CSV format was chosen for its simplicity and flexibility, as it can be easily imported into a variety of GIS, statistical, database or other software for analysis. The frequency and depth of breathing may be calculated quite easily from the raw airflow data, and combined with the recorded concentration of traffic pollutants in order to calculate a value for 'exposure'. This 'exposure' data can then be used alongside the GPS track in order to create a 'personal exposure map' that illustrates exposure to traffic pollution for an individual and a given journey. An example of such a map is given in Figure 2, collected during the Friday morning rush hour, on circular a route in the area surrounding Lancaster University that takes in the University campus itself, some quiet countryside villages, and the A6 road, which is one of the principal routes into, and out of, Lancaster.

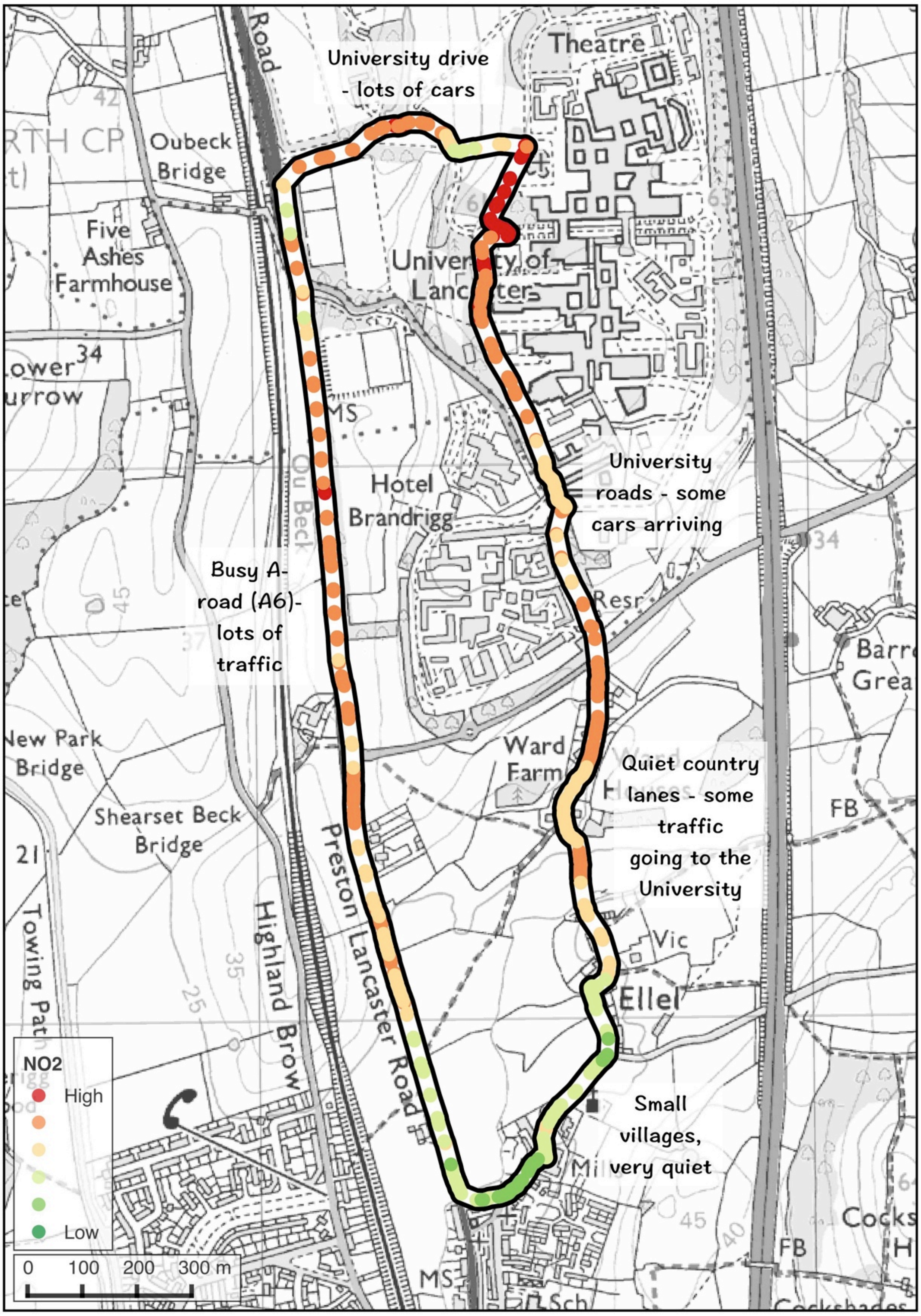

Figure 2. An example 'personal exposure map', showing exposure to NO_2 on a route around Lancaster University at during the morning rush hour. *Base map © Crown Copyright/database right 2014. An Ordnance Survey/EDINA supplied service.*

As expected, Figure 2 clearly shows a decrease in pollution exposure as you move away from the main road and the University, and the highest levels around the car parks within the University itself. This example is intentionally predictable, as it serves to illustrate the principle of the project, and demonstrate the sensors. In a real-world scenario this technique may be applied in order to identify more subtle and less predictable differences in exposure for individuals moving through the urban landscape on real journeys, thus permitting the construction of a 'personal exposure map' for that individual and journey. This may then be used in order to understand patterns of traffic pollution exposure for that individual; as well as in combination with other datasets from other participants, in order to develop a broader understanding of pollution exposure at the city-scale.

3. Discussion and Conclusions

There is no doubt that the inexpensive and non-calibrated sensors used within this study, and others like them, could not be presumed to be of comparable precision or accuracy to their 'professional' counterparts that are available at many times the cost. The benefits of portability and low-cost associated with these sensors, however, outweighs the lower levels of accuracy and precision for the purposes of this project. This is because a typical individual is unlikely to perceive pollution in anything more than a relative scale, whereby a location may have "greater" or "lesser" amount of traffic pollution than elsewhere, but specific values are unknown. Relative accuracy is, therefore, all that is required from the sensors for this purpose. It is for this reason that the values in the 'personal exposure map' in Figure 2 range between 'high' and 'low' as opposed to a numeric scale, which could lead to a 'false confidence' being placed upon the data. It should however, be noted that the development of sensor platforms such as those used within this study is still in the very early stages, and it can be expected that further developments will see an increase in quality along with a reduction in cost and size over the coming years. Indeed, even in the period since the pollution sensors for this project were purchased in late 2013, calibrated versions of the CO and NO_2 sensors have become available, permitting a quantification of quality if required.

Following the analysis described within this paper, it is intended that further work will take place relating to the perception of traffic pollution, and arising changes in behaviour. It is expected, for example, that once their journey is complete, a participant will be interviewed in order to ascertain where in their journey they felt exposed to greater and lesser levels of traffic pollution, and what the reasons for those feelings were. A comparison of ‘measured’ and ‘perceived’ exposure levels will then allow an exploration of the validity of and reasons for participants’ perceptions relating to pollution levels. Such findings may include for example, areas that appear to be ‘unclean’ due to the presence of derelict buildings, but in reality have low levels of pollutants in the air due to lack of vehicular activity; or a city park, which appears ‘natural’, but actually has high levels of traffic pollutants in the air, due to adjacent busy roads. Analysis will also likely take place into whether or not there were any behaviour modifications on the part of participants due to their knowledge relating to pollution exposure, such as a change of route in order to cut out some of the areas of greatest exposure. It is also expected that a follow-up project would include analysis of real-time behaviour change, resulting from the reporting of current pollution exposure via the phone, perhaps by the use of vibration when pollution levels exceed a given threshold. Analysis could then take place into whether or not this causes real-time adjustments in the route taken by a participant, and under what conditions adjustments would be more or less likely to be made.

This project represents a step forward both in the monitoring of personal pollution exposure, and in the understanding of an individual’s perception of the environment surrounding them. Over time, such techniques may be useful for the validation of models such as that proposed by Davies and Whyatt (2014), as well as broadening understanding of perceptions of a wide variety of environmental phenomena through direct sampling, with potential applications far beyond those discussed in this paper.

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5. Biographies

Jonny Huck is a 4^{th} year part-time PhD student researching Geographical Information Science jointly with Imagination Lancaster, and the Lancaster Environment Centre at Lancaster University. His interests include web mapping, fuzzy geography, geospatial visualisation, and the application of new technologies to spatial analysis.

Dr Duncan Whyatt is a Senior Lecturer in GIS within the Lancaster Environment Centre, Lancaster University. His research interests span social and environmental applications of GIS, with specialisms in air pollution.

Dr Paul Coulton is a Senior Lecturer in Design within Imagination Lancaster. His research interests are primarily around experience design, interaction design, and design fictions. His research often encompasses an 'in the wild' evaluation methodology utilising 'app stores' and social networks as an experimental platforms.

Adrian Gradinar is a 1st year PhD student at Lancaster University, researching around The Internet of Things within the Digital Public Space, especially how digital information can be integrated with familiar objects. He is also interested in how digital games could be interconnected with the physicality of the surrounding world.