Context Detection, Categorization and Connectivity for Advanced Adaptive Integrated Navigation

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BIOGRAPHY

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Henry Martin is a PhD student at UCL. His project is concerned with improving navigation performance from a low-cost MEMS IMU. He is interested in inertial navigation, IMU error modelling, multi-sensor integration and calibration algorithms. He holds a Master of Mathematics (MMath) degree from Trinity College at the University of Oxford and an MSc in Advanced Mechanical Engineering from Cranfield University.

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ABSTRACT

This paper lays the foundations for context-adaptive integrated navigation. This enables a navigation system to adapt to different environments and host vehicle behaviour, known collectively as context, to boost accuracy and reliability under challenging conditions. A context-adaptive system detects its operating context and configures its navigation algorithms accordingly.

A five-attribute framework for the categorization of both environmental and behavioural context is proposed, upon which a standard set of context definitions could be built. This would enable the interoperability of subsystems produced by different organisations.

To improve context determination, the concepts of context connectivity, association and scope are introduced. Context connectivity represents the practicality of transitions between different pairs of context categories. Context association provides a way of linking environments to behaviours and vehicles to activities. The scope defines the set of context categories supported by a particular algorithm or which a particular navigation system is expected to encounter. A multi-hypothesis approach to context determination is also proposed.

The results of preliminary context detection experiments using GNSS, Wi-Fi and inertial sensors are presented. It is shown that GNSS C/N_0 measurements may be used to distinguish indoor from outdoor environments and to distinguish different types of outdoor environment. Wi-Fi measurements can also distinguish between different outdoor environments. Vibration spectra derived from accelerometers measurements are shown to be useful for distinguishing between stationary devices placed on a table, held by a pedestrian and placed in a car or bus. They can also distinguish a moving from a stationary car.

1. INTRODUCTION

Context is the environment that a navigation system operates in and the behaviour of its host vehicle or user. Table 1 shows some examples. To meet the demand for greater accuracy and reliability in ever more challenging environments and take advantage of the increasing availability of computational power, integrated navigation systems are becoming more complex [1][2]. As part of this, new positioning techniques are being developed that are much more dependent on the operating context. At the same time, there is a growing demand for systems that can operate in a range of different contexts, adapting accordingly.

Table 1: Examples of contexts

Environment	Behaviour
Urban street	Pedestrian walking
Bottom of the sea	Stationary autonomous underwater vehicle
Open land	Car driving on a highway
The air over the ocean	Airliner flying

Context is critical to the operation of a navigation or positioning system. The environment affects the types of signals available. For example, global navigation satellite system (GNSS) reception is poor indoors while Wi-Fi is not available in rural areas, in the air or at sea, and distance measuring equipment (DME) reception is better in the air than on the ground. In underwater environments, most radio signals do not propagate at all so acoustic signals are used instead. Processing techniques can also be context dependent. In open environments, non-line-of-sight (NLOS) reception of GNSS signals or multipath interference may be detected using consistency checking techniques based on sequential elimination. In dense urban areas more sophisticated algorithms are required, both for NLOS/multipath detection [3] and for accurate GNSS positioning more generally [4].

Environmental feature matching is inherently context-dependent with different types of feature available in different environments. Suitable algorithms, databases and sometimes sensors must all be selected. For example, terrain referenced navigation (TRN) typically uses radar or laser scanning in the air, sonar or echo sounding at sea and barometric pressure on land. Similarly, map matching is very different for cars and pedestrians, while algorithms and databases for image-based navigation vary with the environment, depending on the types of feature available.

Behavioural context is also important and can contribute additional information to the navigation solution. For example, cars normally remain on the road, effectively removing one dimension from the position solution. Their wheels also impose constraints on the way they can move, reducing the number of inertial sensors required to measure their motion [5][6]. Similarly, pedestrian dead reckoning (PDR) using step detection depends inherently on the characteristics of human walking [7]. Host vehicle behaviour is also important for tuning the dynamic model within a total-state navigation filter and for detecting faults through discrepancies between measured and expected behaviour [2]. Within a GNSS receiver, the behaviour can be used to set tracking loop bandwidths and coherent correlator accumulation intervals, and to predict the temporal variation of multipath errors [8]. Where an antenna is placed on a vehicle or person [9] can also affect performance.

Historically, context was implicit; a system was designed to be used in a particular type of vehicle, handling its associated activities and environments without the need for adaptation. However, as integrated navigation systems become more complex, explicit consideration of context is becoming important for three reasons. Firstly, there is a move towards navigation systems that can operate in a variety of different contexts. For example, the smartphone moves between indoor and outdoor environments and can be stationary, on a pedestrian, or in a vehicle [10]. Similarly a small surveillance drone may be required to operate from above, amongst buildings, or even indoors.

Secondly, a large number of the new navigation and positioning techniques that have emerged since the turn of the century only work in certain contexts. For example, GNSS shadow matching [11][12][13] can improve the cross-street positioning accuracy in urban environments, but brings no benefit in open areas. Similarly, road vehicle positioning techniques based on sign recognition, magnetic anomalies and barometric TRN [14] are of little use for air navigation. Furthermore, some techniques, such as PDR using step detection and vehicle motion constraints, will give wrong information when the assumed and actual contexts diverge.

Finally, as the number of navigation and positioning applications grows, there is a need to re-use hardware and software modules across multiple applications to reduce development and production costs [15].

A context-adaptive positioning or navigation system detects its operating context and reconfigures its algorithms accordingly. This is sometimes known as cognitive positioning or navigation. Figure 1 illustrates the concept. Different types of environments can be distinguished based on the strengths of various classes of radio signal and the directions from which GNSS signals are receivable. Vehicle types can be identified from their velocity and acceleration profiles and by vibration signatures derived from phenomena such as engine vibration, air turbulence, sea-state motion, and road-surface irregularity.

Based on the detected context, a navigation system may adapt its operation by selecting different radio positioning signals and techniques, processing inertial sensor data in different ways, selecting different map-matching algorithms, and varying the tuning of the integration algorithms. Table 2 shows an example scenario for a smartphone. Note that the behavioural context refers to the motion of the vehicle or pedestrian that the smartphone is attached to, not the device itself. Thus in this scenario, the smartphone’s behaviour changes from that of a stationary object via that of a pedestrian to that of a car.

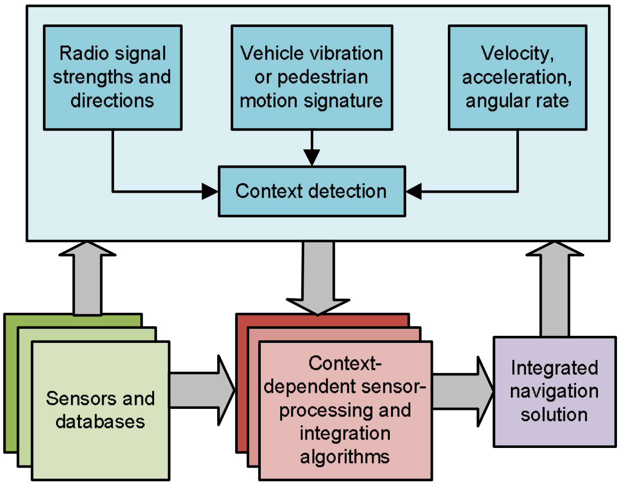

Figure 1: A context-adaptive navigation system [2]

Table 2: Example scenario for a context-adaptive smartphone navigation system

Action	Context change detected	Navigation system response
System on a table indoors	Fixed location indoors	Previous position solution used
Picked up by a pedestrian	Pedestrian behaviour	Activate indoor radio positioning and PDR using step detection
Pedestrian walks	Walking forward	Activity input to PDR algorithm
Pedestrian goes outside	Land outdoor environment	Deactivate indoor radio positioning; activate GNSS
Pedestrian sits in a car	Stationary pedestrian	Assume position hasn't changed
System placed on car dashboard	Fixed location	Deactivate PDR
Car engine starts	Stationary car	
Car drives away	Urban driving	Activate car map matching and car motion constraints

Previous work on context-adaptive navigation and positioning has focused on individual subsystems. For example, there has been substantial research into determining the motion type and sensor location for PDR using step detection [16][17][18][19][20]. Researchers have also begun to investigate context-adaptive (or cognitive) GNSS [8][24][25].

This paper considers context adaptation across an integrated navigation system as a whole. In context-adaptive *integrated* navigation, multiple subsystems will both make use of context information and contribute to the context determination process, sharing context information across the whole system. These subsystems will often be produced by different organisations. Therefore, it is essential to ensure that common context definitions are used throughout the integrated system. Section 2 therefore proposes a context categorization framework on which a standard set of context definitions could be built. Environmental and behavioural context are addressed in turn. The concepts of context association and scope are then introduced which reduce the number of contexts to consider.

Section 3 then introduces the concept of context connectivity. This minimizes false or ambiguous context identification by using the fact that it is only practical to transition directly between certain pairs of contexts. For example, it is not normally possible to move directly from an airborne to an indoor environment as an aircraft must land first. Thus, the air and land contexts are connected, as are the land and indoor contexts, but the air and indoor contexts are not. Location-dependent connectivity takes this a step further by considering that some context changes only happen in certain places. For example, people normally board and leave trains at stations.

Section 4 describes context detection and determination. The literature is reviewed and experimental results are presented on environmental context detection using GNSS and Wi-Fi, followed by behavioural context detection using inertial sensors. How to determine the context from multiple detectors, the previous context and connectivity information is then discussed.

Finally, Sections 5 and 6, summarise the conclusions and the future work that must be undertaken to make context-adaptive integrated navigation a reality.

2. CONTEXT CATEGORIZATION

In order to implement a multisensor navigation system with many different subsystems adapting to the context and contributing to the context determination process, it is necessary to agree a common set of context categories and their definitions. Standard context definitions are also needed simply to enable software modules to be re-used across multiple applications [15].

A context framework for navigation and positioning must be designed specially in order to be fit for purpose. Context frameworks designed for mobile computing in general are not suitable. Each context category must map to a configuration of the navigation system; otherwise, it serves no purpose. However, multiple categories may map to the same configuration as different navigation systems will respond to context information in different ways. It may also be useful to divide context categories in order to support context determination through connectivity. In a fully autonomous context-adaptive navigation system, each context category must also be independently identifiable using detection algorithms and connectivity information. However context information from the host vehicle control system may also be used where available. The boundaries between context categories must therefore be clearly definable in terms of both detection criteria and how they are used.

Environmental and behavioural context are fundamentally different. Environmental context is concerned with the availability of signals and other features that may be used for determining position whereas behavioural context is concerned with motion. Therefore, they should be treated separately in a context categorization framework.

The behavioural context may be divided into the vehicle type and the activity undertaken by that vehicle. For pedestrian navigation, different parts of the body move quite differently, so sensor location on the body can be considered analogous to vehicle type.

Context may also be considered at different levels. In some cases, it is sufficient to consider context in broad classes such as indoor or outdoor and air, land or sea. In other cases, a finer granularity is needed, specifying the type of indoor environment or the type of aircraft. Therefore, a two level context categorization framework is proposed, comprising class and type. For behaviour, a common set of classes containing separate vehicle and activity types is proposed. A third level may or may not be needed, but is not considered further here.

Figure 2 depicts the overall framework. A context category thus has up to five attributes: environment class, environment type, behaviour class, vehicle type and activity type.

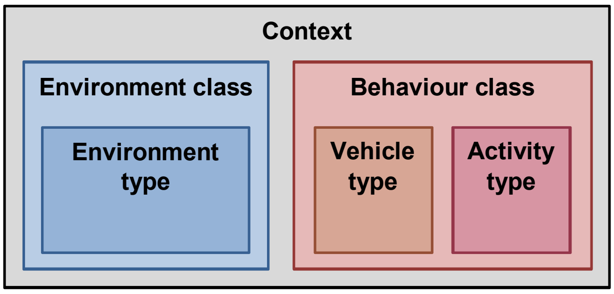

Figure 2: Proposed attributes of a context category

Further attributes that are relevant to adaptive navigation systems, but not included within the context framework proposed here are operating conditions and user requirements. Operating conditions include interference to or jamming of GNSS or other types of radio signal, acoustic interference, fog or cloud cover, air turbulence, sea states and bumpy roads. Many of these operating conditions only affect a single subsystem, such as GNSS. Therefore, it can be argued that it is better to handle them within that subsystem rather than burdening the context management infrastructure of the integrated navigation system with further information. A counter argument is that if one subsystem is degraded, the others must be weighted higher within the integrated navigation solution. Counter to this is the argument that all subsystems should provide error covariance information, enabling the reweighting to occur without directly using context information. This also facilitates the detection of faults by comparing solutions from different subsystems.

Vibration levels and frequency profiles are relevant to multiple subsystems. However, as vibration is a continuous parameter, whereas context is largely discrete, there is an argument that vibration information should be distributed separately. One option is to include it with the integrated navigation solution fed back to the subsystems. Note that vibration is useful for context detection.

Where hardware and software modules are re-used across multiple applications, different user requirements will typically be applied and must be conveyed to those modules [15]. There may also be a need for a given navigation or positioning system to meet different requirements for different tasks, such as smartphone apps. Requirements may be distributed in a similar way to context information. It is thus for the navigation and positioning community to decide whether requirements should be incorporated within the context framework or treated separately.

The remainder of this section explores environmental and behavioural context classification in more detail and then discusses context association and scope.

2.1 Environmental Context

The environmental context may be divided into six broad classes: indoor, land (outdoor), on water, underwater, air and space. This is unlikely to provoke controversy. However, the environment type classification is open to greater debate. The number of types within each class and where the boundaries are drawn must depend on which environments may be distinguished by context detection algorithms using data from typically available sensors. Environment type categories must also be useful for determining the configuration of an integrated navigation system. Thus, the category could provide an indication of the types of signals and environmental features available for positioning.

Table 3 lists a possible set of type categories for each environment class and describes some (but not all) of their characteristics in terms of the information available for position fixing. Numbering the types enables intermediate types to be defined or ambiguity to be represented using non-integer values. It also provides the option to represent the environment type within each class as a continuous spectrum instead of a series of discrete categories, which may be more representative of real environments. Standardization would then be achieved by agreeing definitions for a number of fixed points on the scale. Whether the inland and urban waterway categories are necessary or whether they should be subsumed into the corresponding land environment types is a subject for further debate.

Table 3: Possible environment type categories

Indoor	
Environment type	Characteristics
1. By door or window	Relatively strong GNSS and radio reception
2. Outer room	Some GNSS reception; strong reception of other radio signals from outside
3. Inner room	Very weak GNSS reception; some reception of other signals
4. Deep inside	No GNSS reception; weak reception of other radio signals
5. Very deep inside or underground	No reception of external radio signals
Land Outdoor	
Environment type	Characteristics
1. Open	Good GNSS reception; No Wi-Fi
2. Suburban	Good GNSS; Wi-Fi available
3. Urban	Some disruption to GNSS; Wi-Fi available
4. Dense urban	Poor GNSS; Wi-Fi available
5. Tunnel or Cave	No radio reception
On Water	
Environment type	Characteristics
1. Mid Ocean	Good GNSS; no terrestrial VHF/UHF radio
2. Coastal	Good GNSS; VHF/UHF radio receivable from the shore
3. Harbour/ harbour approach	As above with coastal landmarks visible
4. Inland waterway	Similar to Land Open
5. Urban waterway	Similar to Land Urban
Underwater	
Environment type	Characteristics
1. Sub- surface	Low frequency radio; periscope can be raised
2. Fully submerged	No radio reception; bottom cannot be observed
3. Deeply submerged	No radio reception; bottom observable acoustically
4. On bottom	No radio; height above bottom known
Air	
Environment type	Characteristics
1. Low altitude near airfield	Terrain observable visually (or infra-red); landing signals receivable; good GNSS
2. Low altitude away from airfield	Terrain observable visually (or infra-red); no landing signals; DME unreliable; good GNSS
3. High altitude over land	Terrain not observable; good DME reception; good GNSS
4. High altitude over ocean	Good GNSS; no terrestrial radio reception
Space	
Environment type	Characteristics
1. Launching/ landing	Good GNSS and terrestrial radio reception; surface within radar range
2. Low Earth orbit (below GNSS)	Good GNSS reception
3. Mid Earth orbit (similar to GNSS)	Moderate GNSS reception
4. High Earth orbit (above GNSS)	Poor GNSS reception
5. Deep space	No GNSS reception

2.2 Behavioural Context

The behavioural context may be divided into seven broad classes: fixed location, pedestrian, land vehicle, ship or boat, underwater vehicle, aircraft and spacecraft. At first sight, these appear to correspond to the environment classes, raising the question of why separate environment and behaviour classes are necessary. However, an aircraft can be on the ground, while pedestrians and most land vehicles can be either indoors or outdoors.

Table 4 lists possible vehicle and activity types for the land vehicle, ship or boat, underwater vehicle, aircraft and spacecraft classes. It is intended primarily to stimulate debate, so merger, subdivision and addition of categories is likely to occur following further research and discussion. Further work will then be needed to specify each category quantitatively. As with environmental context, both ease of detection and the need to adapt the navigation system configuration must be considered in determining the behavioural context categories. For example, the proposed road vehicle category comprises cars, vans, trucks or buses with internal combustion engines, which have broadly similar behaviour and can be identified through engine vibration. Subdivision may or may not be needed. A separate category has been proposed for electric road vehicles as they cannot be detected by engine vibration in the same way.

Table 4: Possible vehicle and activity types for the vehicle behaviour classes

Land Vehicle	
Vehicle types	Activity types
Road vehicle	Stationary (engine off)
Electric road vehicle	Stationary (engine on)
Train	Parking
Off-road vehicle	Urban driving
Motorcycle or scooter	Rural driving
Bicycle	Highway driving
Wheelchair	Off-road driving
	Turning {left; right}
	Rail travel
	Changing tracks{left; right}

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Table 4: Possible vehicle and activity types for the vehicle behaviour classes *Continued*

Boat or Ship	
Vehicle types	Activity types
Sailing Yacht	Stationary
Speedboat	Drifting
Canoe	Moving forward
Rowing Boat	Manoeuvring with thrusters
Ship	Turning
Hovercraft	
Offshore platform	
Underwater Vehicle	
Vehicle types	Activity types
Large	Stationary
Medium	On the bottom
Small	Drifting
	Powered movement
Aircraft	
Vehicle types	Activity types
Micro air vehicle (MAV)	Stationary (engine off)
Helicopter	Stationary (engine on)
Glider	Taxiing
General aviation aircraft	Taking off
Airliner of Cargo plane	Landing
Combat aircraft	Flying
Reconnaissance aircraft	Hovering
Guided weapon	
Spacecraft	
Vehicle types	Activity types
Launch vehicle	Launching
Satellite	Manoeuvring
Space station	Orbiting or free falling
Space probe	Landing
Planetary lander	

Considering the need for different categories, different vehicle types undertaking different activities require different tuning of the dynamic model within a total-state navigation filter and different thresholds for detecting faults in the integrated and subsystem navigation solutions. For road vehicles, the amount of wheel slip depends on the activity and affects the application of motion constraints [27]. Minor differences in these tuning parameters and thresholds do not merit separate type categories, whereas larger differences do.

Different types of land vehicle also require different approaches to map matching, while detection of turning and parking activities can aid the process. For example, a parking car is more likely to be off the road network. Map matching is also applicable to boats on inland waterways and taxiing aircraft.

Table 5 lists sensor locations and activity types for the pedestrian class [2]. This is based on research into PDR using step detection for which the step-length estimation algorithms are context-dependent [16][17][18]. Thus, it is more mature than for the other behaviour classes. Sporting activities have been omitted to save space and may justify the creation of an additional class.

Table 5: Pedestrian class sensor locations and activity types

Pedestrian	
Sensor locations	Activity types
Top of head	Stationary
Shoulder	Walking forward
In an armband	Walking backward
Strapped to back	Sidestep {left; right}
Waistband	Turn {left; right}
Shoe	U-turn {left; right}
Handheld in front	Climbing steps/stairs
Held to ear	Descending steps/stairs
Dangling in the hand, from a wrist-strap or in a hand-held bag	Standing up
	Sitting down
	Lying down
Shirt pocket	Bending over
Trouser pocket	Falling
Loose in a backpack	Running
	Jogging
	Using an escalator
	Using an elevator

2.3 Context Association

Considering every combination of environment type, vehicle type (or sensor location) and activity type, there are tens of thousands of different context categories. It is clearly impractical for a navigation system to detect and respond to all of these categories. The problem can be simplified by detecting and responding to environmental and behavioural context separately. However this still leaves about 30 environmental context categories and several hundred behavioural categories.

In reality, the environment, vehicle and activity types are not completely independent. Certain activities are associated with certain vehicle types and certain behaviours are associated with certain environments. For example, an airliner flies, while a car does not and flying takes place in the air, not at the bottom of the sea. A car typically travels more slowly, stops more, and turns more in cities than on the highway. This information can be used to eliminate combinations of environment type, vehicle type (or sensor location) and activity type that are not associated in practice. This both reduces the number of context categories that a navigation system must handle and reduces the chances of the context determination algorithms selecting an incorrect context.

Within the overall context framework proposed here, associations can be applied in two places. Firstly, within each behaviour class, a vehicle type and activity type may or may not be associated with each other. Secondly, a behaviour class may or may not be associated with an environment class.

Considering, the land vehicle class, any of the vehicle types may be associated with the stationary (engine off) and all except the bicycle, wheelchair and electric car or van with stationary (engine on), noting electric motors do not operate when the vehicle is stationary. All of the road vehicle types are associated with parking, urban driving, rural driving, highway driving and turning. However, only off-road vehicles are associated with off-road driving. The normal motion of a bicycle and wheelchair could be classed as urban driving and parking respectively; alternatively, separate activities could be specified for them. A train may be associated with rail travel and changing tracks. Finally, all vehicle types, except possibly trains, may be associated with turning.

For the other vehicle classes listed in Table 4, most activities may be associated with most of the vehicle types in that class. Exceptions include manoeuvring with thrusters, as only ships and offshore platforms are equipped with these; hovering, which only MAVs and helicopters are capable of; and spacecraft landing, which only some launch vehicles and planetary landers are associated with.

All of the pedestrian activities listed in Table 5 may be associated with all of the listed sensor locations. However, sporting activities, which are not listed here, would be associated with a different set of sensor locations. The same applies to activities, such as climbing, crawling and walking while ducking associated with military and rescue personnel.

Table 6 and the accompanying notes show the associations between the environmental and behavioural classes. Note that some associations are at the class level and some are at the type level.

Table 6: Associations between environment and behaviour classes

Behaviour class	Environment class					
	Indoor	Land outdoor	On Water	Under-water	Air	Space
Pedestrian	Yes	Yes	Note 1	Note 1	Note 1	Note 1
Land	Note 2	Yes	Note 3	No	No	No
Boat/ship	Note 4	Note 4	Yes	No	No	No
Underwater	Note 4	No	Yes	Yes	No	No
Aircraft	Note 2	Yes	Note 5	No	Yes	No
Spacecraft	Note 2	Yes	No	No	Note 6	Yes
Fixed	Yes	Yes	No	Note 7	No	No

1) A pedestrian can be moving within a large vehicle in these environments.
2) Vehicles can enter indoor environments; though only undertake some types of activity there.
3) A land vehicle can be moving on a ship or boat, such as a ferry, (a vehicle can also move inside a large aircraft, but only when it is on the ground).
4) Boats, ships and underwater vehicles can be on land or indoors, but do not exhibit class behaviour in those environments.
5) Some aircraft can land, take-off and taxi on water.
6) Spacecraft launch from and land in the air, but do not undergo all types of activity there.
7) A fixed location can be on the bottom of the sea or a river bed, but not in the other types of underwater environment.

In practice, a system of context association must consider three categories: normal, abnormal but possible and impossible. Thus, it is normal for a land vehicle to be associated with a land outdoor environment, possible but abnormal for it to be underwater and impossible for it to be in orbit. Detection of abnormal associations could be used to trigger alerts.

2.4 Scope

It is not necessary for a set of navigation and positioning algorithms to respond to every conceivable context, just those categories that the host system is designed to operate under. The same applies to the context detection and determination algorithms. To ensure that suitable algorithms are used, context specifications should be produced that state which contexts are required and which are supported by the navigation and positioning algorithms and the context detection and determination algorithms. The supported contexts would then be matched against the required contexts as part of the system design process. In a modular system [15], context specifications for each module would need to be produced and compared against the requirements.

Limiting the scope of a navigation system’s context can also be used to aid context determination by forbidding context categories that cannot occur for that particular system. For example, for a navigation system designed only for an airliner, the on water, underwater and space environmental classes and the pedestrian, land vehicle, boat/ship, underwater vehicle, spacecraft and fixed location behavioural classes would all be forbidden.

A context requirement specification should therefore define each of the standard context categories to be one of the following:

- Required – The navigation system must detect this context category and respond to it;
- Unsupported – This context category could conceivably occur, but the navigation system is not required to detect and respond to it;
- Forbidden – This context category cannot occur.

Figure 3 presents a possible context requirement specification for a smartphone. Note that for many applications, some of the context requirements would need to be specified at the type level as opposed to the class level.

Environment:
- ↳ Indoor: Required
- ↳ Land Outdoor: Required
- ↳ On Water: Unsupported
- ↳ Underwater: Forbidden
- ↳ Air: Unsupported
- ↳ Space: Forbidden

Behaviour:
- ↳ Fixed Location: Required
- ↳ Pedestrian: Required
- ↳ Land Vehicle: Required
- ↳ Boat or Ship: Unsupported
- ↳ Underwater Vehicle: Forbidden
- ↳ Aircraft: Unsupported
- ↳ Spacecraft: Forbidden

Figure 3: A possible context requirement specification for a smartphone

3. CONTEXT CONNECTIVITY

One way of minimising incorrect context determination is to only permit selection of context categories that are directly connected to the previous category, i.e. where a direct transition between those categories is permitted. Thus, an inner room environment is directly connected to an outer room environment, but not to a fully submerged environment. Similarly, stationary vehicle behaviour is connected to pedestrian behaviour, whereas moving vehicle behaviour is not because a vehicle must normally stop to enable a person to get in or out. Context connectivity is directly analogous to the road link connectivity used in map matching [26] and a similar mathematical formulation may be used. Connectivity can thus be thought of as a way of representing the topology of the context categories. Figure 4 shows the connectivity of the environment type contexts.

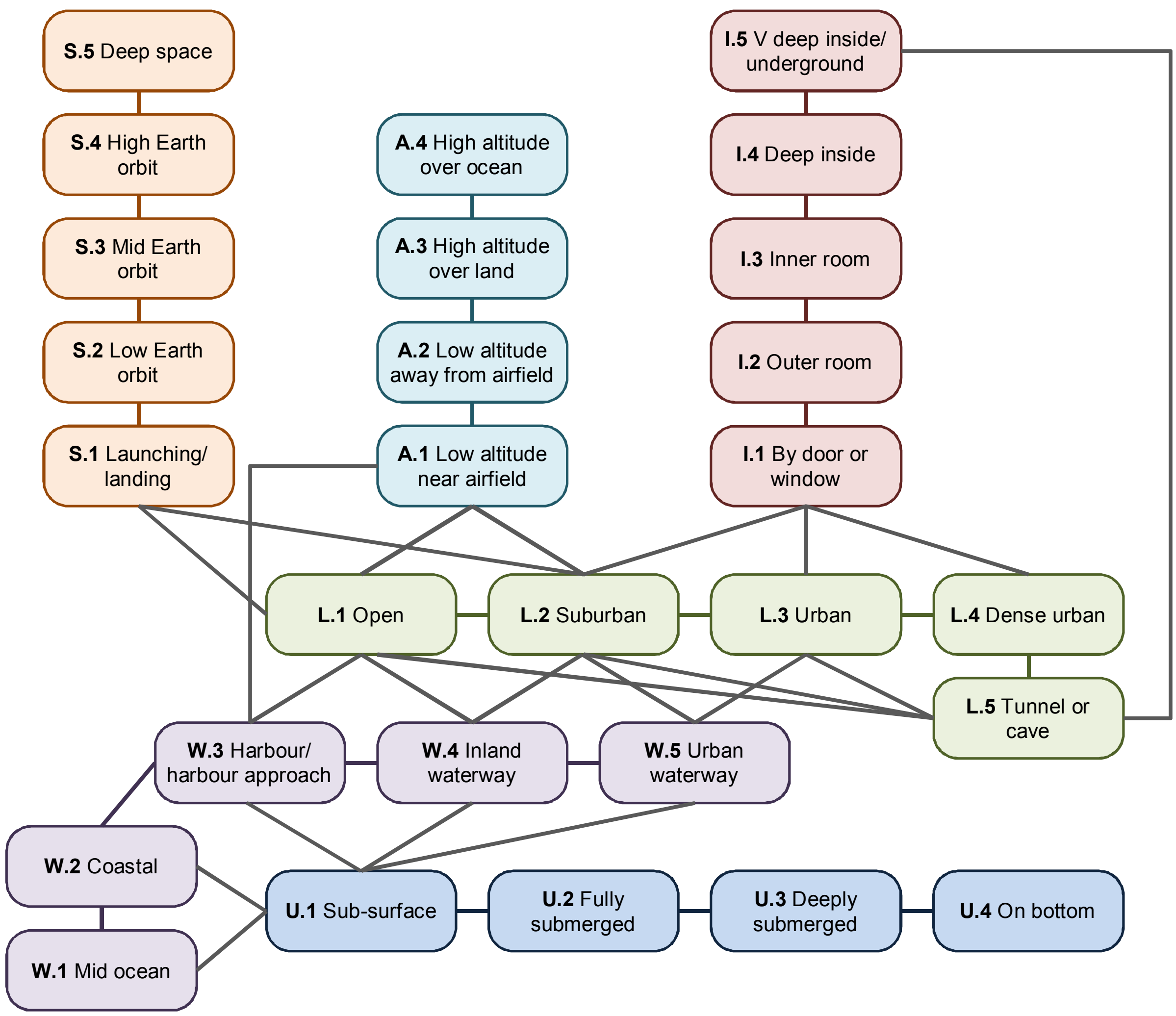

Figure 4: Connectivity of environment type categories

Although connectivity constraints will generally reduce the number of incorrect context selections, a simple implementation can occasionally result in the system being stuck on an incorrect context category following a faulty selection. This can occur when the correct context category is not directly connected to the incorrectly selected category and the intermediate category is a poor match to the measurement data. One solution is for the context determination algorithm to permit the selection of indirectly connected context categories in cases when both the previously selected category and all those directly connected to it are poor matches. Another option is to represent connectivity as continuously valued transition probabilities between context categories instead of a simple Boolean context. Categories connected via an intermediary can then be given low non-zero transition probabilities between them to facilitate recovery from incorrect context category selections. This also facilitates the representation of transitions between context categories that are rare, but not impossible.

Context determination reliability may be further enhanced by considering location-dependent connectivity. For example, people normally board and leave trains at stations and fixed-wing aircraft typically require an airstrip to take off and land. As position solutions can be wrong on occasion and maps can become out of date, this approach should be more robust where connectivity is represented as continuous transition probabilities. Location would then be used to modify the probabilities rather than to permit or block transitions.

4. CONTEXT DETECTION & DETERMINATION

There are many different ways of detecting context, with environmental and behavioural detection techniques largely independent of each other. Potentially any sensor can contribute to the context determination process.

Environmental context can potentially be detected using:

- The position solution and a map, noting that the reliability of this depends on the accuracy of both;
- The types, numbers and strength of the receivable radio signals;
- Features of the environment detecting using cameras, laser scanners, radar or sonar;
- Ambient light, sounds and odours;
- Air or water pressure.

The vehicle type and activity type aspects of the behavioural context must be detected together, except where the vehicle type is fixed and known, which may be incorporated in the context scope (Section 2.4) Behavioural context can potentially be detected using:

- The velocity solution, acceleration, roll and pitch angles, and angular rate;
- Statistical analysis of inertial sensor signals;
- Information from the host vehicle control system.

In this section, environmental context detection using GNSS and Wi-Fi and behavioural context detection using inertial sensors are examined in more detail. In each case, the literature is summarised and new experimental results presented. The section concludes with a discussion of how the reliability of context determination may be improved by considering multiple hypotheses

4.1 Environmental Context Detection using GNSS

In [8], it is shown that both C/N_0 measurements and a Rician K-Factor estimator [28] may be used to distinguish environment inside a wooden house from an outdoor environment. Here, a C/N_0-based approach to environmental context detection is adopted as C/N_0 measurement is a standard feature of GNSS receivers.

C/N_0 measurement data was collected from all GPS signals received by a Sony Xperia Active Android smartphone at 15 different locations in various indoor, urban and open environments. About 100s of data was collected at each site. Figure 5 presents histograms of the C/N_0 measurements.

A number of trends may be identified from these histograms. As expected, the average received C/N_0 is lower in indoor environments than in urban environments and lower in urban environments that in open environments. From this data, it can be seen that an average C/N_0 of less than 25 dB-Hz is characteristic of an indoor environment, while an average C/N_0 of greater than 30 dB-Hz is characteristic of a more open environment. It can also be seen that the standard deviation of the measured C/N_0 (in dB-Hz) is generally less for the indoor environments than those outdoors. Thus, both the mean and standard deviation of the measured C/N_0 across all of the GNSS satellites tracked are useful for environmental context detection.

The use of the total measured C/N_0, summed across all of the satellites received was also considered as a context metric. This was typically less than 200 dB-Hz (for GPS satellites only) indoors and greater than 200 dB-Hz outdoors. However, significant fluctuations were observed over each 100s data collection period; Figure 6 shows an example. Therefore, this is not considered a reliable metric. Possible causes are changes in body masking as the user moves around and holds the phone differently [9], and variations in signal obstruction by passing people and traffic.

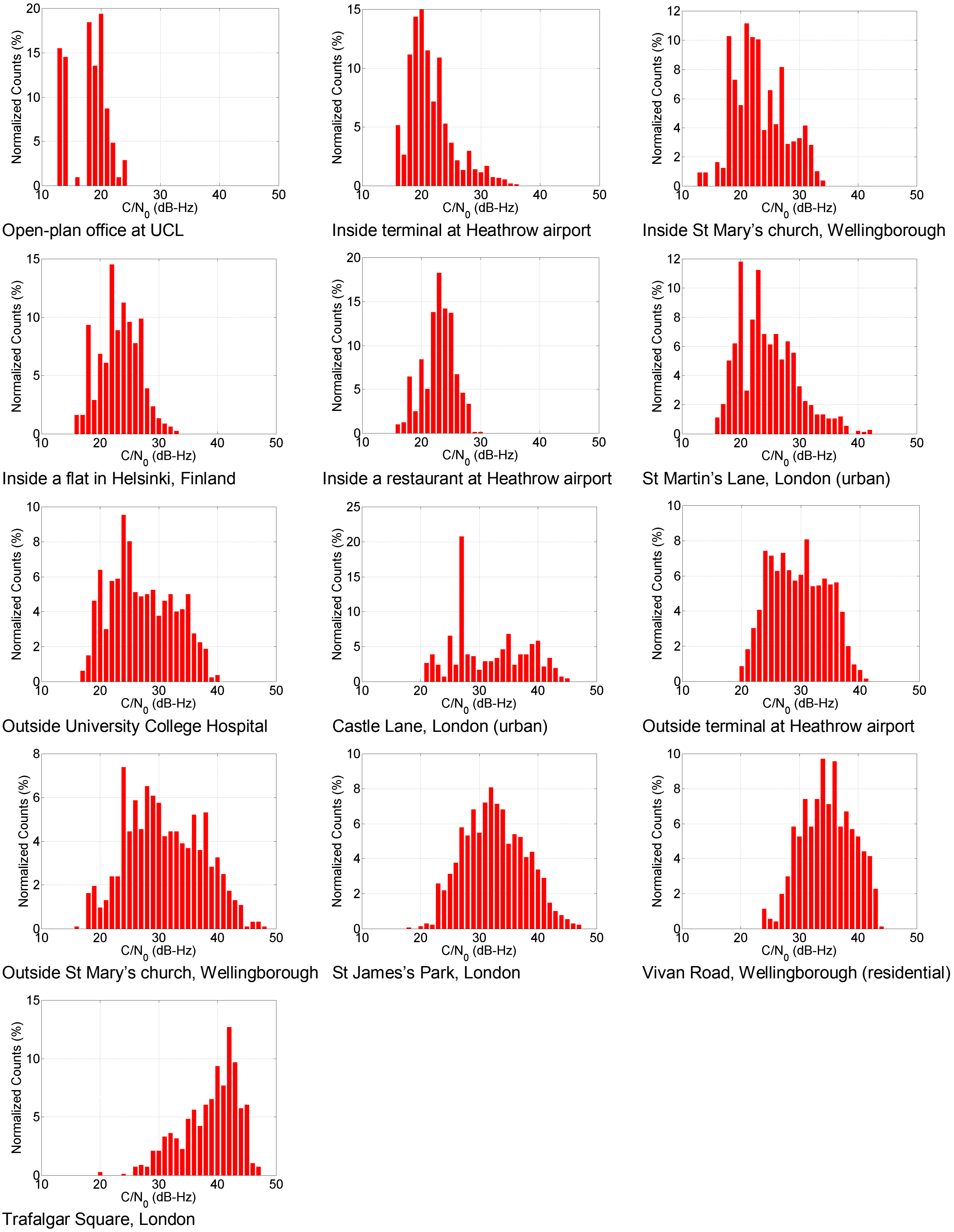

Figure 5: C/N_0 measurement distributions at various indoor, urban and open locations. Note that St Mary’s Church is in a suburban area.

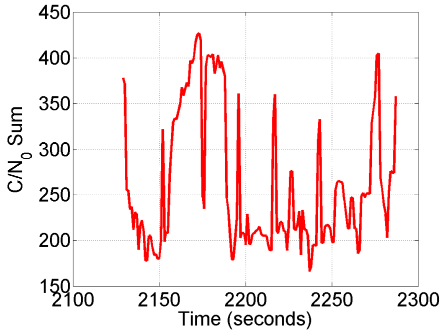

Figure 6: Total GPS measured C/N_0 in St James's Park, London

4.2 Environmental Context Detection using Wi-Fi

The vast majority of smartphones are equipped with Wi-Fi, which may be used for positioning where a suitable database is available [2]. For context detection, one might expect to see different patterns in the number, strength, type and name of the access points detected, in different kinds of environments. Typically in rural environments no Wi-Fi signals will be received, thus a combination of no Wi-Fi and good GNSS may indicate a rural area, but Wi-Fi-based context detection could be much more useful in cities, where one can usually receive multiple networks both indoors and out.

In [24], three different metrics for distinguishing between indoor and outdoor environments using Wi-Fi were tested:

- The number of access points received;
- The moving average of the signal to noise ratios (SNRs) of the 10 strongest signals;
- The standard deviation of the SNRs of all of the received signals.

All three metrics were assumed to be greater indoors than outdoors. However, it was found to be difficult to distinguish an indoor environment from the area directly outside the test building using a single metric. Better performance was obtained using a combination of the three metrics.

Here, a study was conducted using an Android application, written in house, on a Sony Xperia active phone. For each access point received the application recorded: the time; the unique hardware ID number (SSID); the broadcast "name" of the access point; the signal strength (in dBmW); the type of encryption; and the frequency at which the communication was taking place (in MHz). This information was imported into MATLAB. Data was collected in the same locations and at the same time as the GNSS tests described in Section 4.1.

To distinguish indoor and outdoor environments, one might reasonably expect to observe a pattern where outdoors there are lots of mid- and low-strength signals whereas indoors there are a few strong signals and remaining signals are weak and few in number. This hypothesis was tested on data collected at several locations. It is certainly possible to observe a general reduction in signal strengths (and numbers of points detected) in data collected just outside the entrance to a building, compared to just inside the entrance. However, the magnitude of these differences is hard to distinguish from other factors which have a large effect on detected signal strength such as body-masking effects from how the mobile device is held (over the head vs. cupped by both hands to read the screen in bright sunlight), and other temporary environmental changes such as crossing the street.

Figures 7, 8 and 9 show the number of Wi-Fi access points received as a function of signal strength in indoor, urban, and suburban environments, respectively. There are clear differences between the indoor and suburban datasets, with the average signal strength in the suburban environment significantly weaker. However, in this case, the urban Wi-Fi dataset is closer to the indoor dataset than the suburban dataset. Thus Wi-Fi based context detection may be more useful for distinguishing between different types of outdoor environment than for distinguishing between indoor and outdoor environments. Further data is needed to establish whether this is the case.

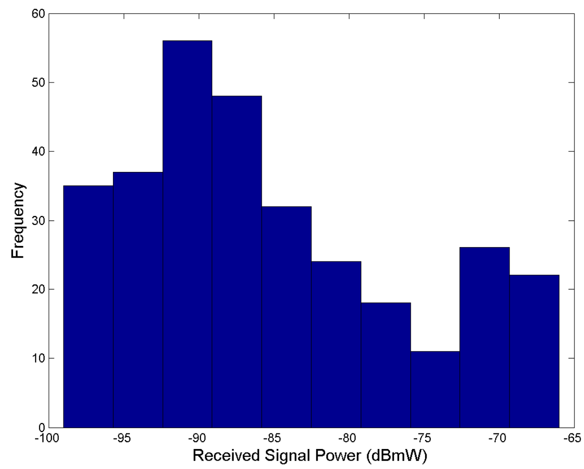

Figure 7: Wi-Fi received signal strength distribution in a residential indoor environment, a flat in Helsinki, Finland

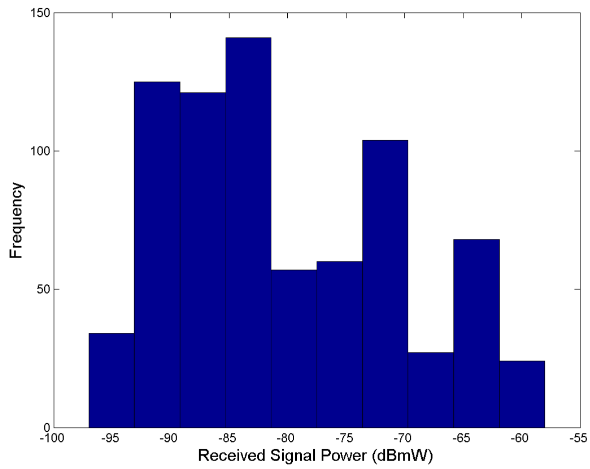

Figure 8: Wi-Fi received signal strength distribution in an urban environment, St Martin's Lane, London

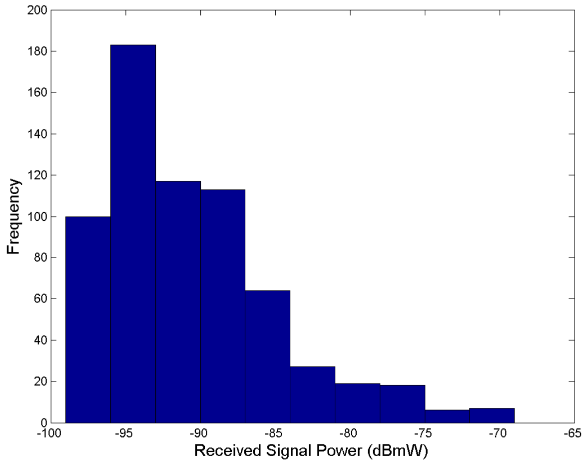

Figure 9: Wi-Fi received signal strength distribution in a suburban environment, a residential street in Wellingborough

Table 7: Wi-Fi access point names in suburban residential and urban business environments

Residential Street in Wellingborough	St Martin's Lane, London (urban business district)
'virginmedia0604562'	'virginmedia4419048'
'BTHomeHub2-KRT5'	'PREZZOCNET'
'BTOpenzone-H'	'BTWifi-X'
'TALKTALK-6920A4'	'Euronews'
'TALKTALK-378738'	'Auto-BTWiFi'
'virginmedia5255440'	'BTOpenzone'
'SKY8A352'	'Auto-BTWiFi'
'virginmedia0970316'	'BTOpenzone'
'BTWiFi-with-FON'	'O2 Wifi'
'161Wireless'	'SpaghettiHouseStMartins'
'SKY57F2F'	'BTWifi-X'
'BTHub3-7FXH'	'Auto-BTWiFi'
'BTWiFi-with-FON'	'Beanstalk_Guest'
'SKYAAB13'	'TecturaWiFi'
'BTWiFi-with-FON'	'Redwood_Guest'
'BTWiFi'	'BTOpenzone'
'SKYDDBE2'	'BTWifi-X'
'virginmedia8056671'	'Wells'
'TALKTALK-06A74F'	'4CE676CC9F99'
'BTHub3-93RT'	'Auto-BTWiFi'
'anthony'	'yellow000pluto'
'BTWiFi-with-FON'	'BTHub3-Z8KH'
'BTWiFi'	'BTHomeHub2-9X9K'
'TALKTALK-264904'	'BTOpenzone'
	'BTOpenzone'
	'GARFUNKELS_FREE_WIFI'
	'Mozilla-G'
	'Mozilla Guest'

One very simple, yet effective, technique to distinguish business districts from residential is to categorize the broadcast "names" of the access points, into "default names" and "others". The typical domestic customer of an internet service provider (ISP), receives a router from their ISP with a default "name" and randomly generated password out of the box, this "name" is typically a predictable combination of the name of the ISP followed by a short random string. While it is possible to change this name, our experiments show that few domestic consumers do. In Table 7, a typical epoch is presented from a suburban data set and an urban one. The vast majority of networks in the suburban dataset have names with the format "SKY…" "virginmedia…" "TALKTALK-…" "BTHomeHub…", while this is less common in the urban dataset where a significant number are named after businesses such as 'PREZZOCNET', 'SpaghettiHouseStMartins', and 'GARFUNKELS_FREE_WIFI', all of which are restaurants on that street, and the two ending '…_Guest' presumably belong to the hotel there.

Another possible technique to distinguish business from residential environments is by the proportion of open networks. One might reasonably expect a central urban area to have more open networks in cafes or other public places. This metric is, in practice, slightly corrupted by ISPs using their domestic consumer's routers to broadcast their own 'cloud'-type service. However, these can easily be eliminated by discounting those routers whose hardware ID numbers are similar (in the sense that they differ by only a single hex pair) (see Table 8). The green and magenta lines in Figures 10 and 11 illustrate this.

Table 8: Three access points received at a single epoch, presumed to be from the same router (signal strength is in dBmW)

ID	Name	Signal Strength	Encryp-tion
cc:96:a0:36:f6:1a	BTHub3-WP9K	–94	WPA
8a:96:a0:36:f6:1c	BTWiFi-with-FON	–95	open
8a:96:a0:36:f6:1b	BTWiFi	–95	open

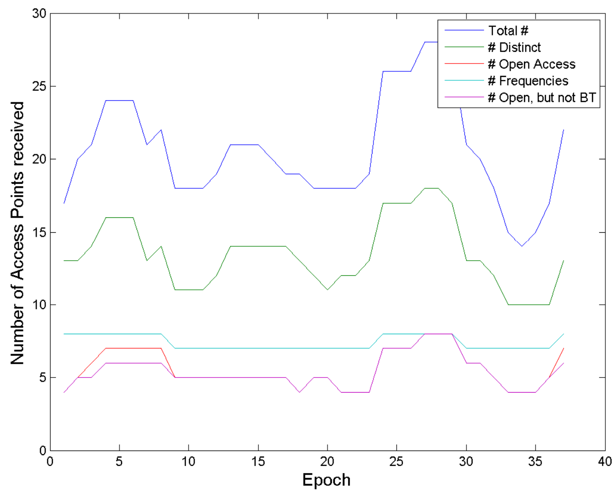

Figure 10: Wi-Fi received signal strength distribution in an urban environment, St Martin's Lane, London

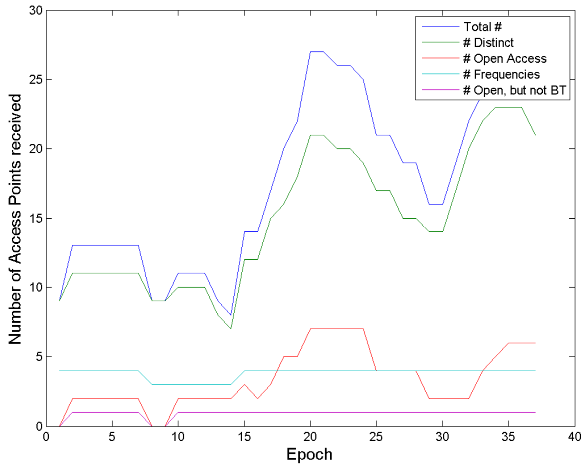

Figure 11: Wi-Fi access point categories in a suburban residential environment, Vivan Road, Wellingborough

4.3 Behavioural Context Detection using Inertial Sensors

Extensive research on context detection for pedestrian navigation has already been conducted to support PDR using step detection [16][17][18][19][20]. Knowledge of both the sensor location and activity is required in order to estimate the distance travelled from the detected motion; thus PDR is doubly context-dependent [2]. A three-step process is typically implemented:

- Firstly, orientation-independent signals are generated from the sensor outputs. Options include the magnitudes of the accelerometer and gyro triads, $|\mathbf{f}_{ib}^{b}|$ and $|\boldsymbol{\omega}_{ib}^{b}|$, and the 'dynamic acceleration', $|\mathbf{f}_{ib}^{b}|-g_b$. Separate horizontal and vertical signals may be used where the sensor orientation is known,
- Secondly, the characteristics of each signal are determined from a few seconds of data. The mean, standard deviation, root mean squared (RMS), inter-quartile range, mean absolute deviation, maximum–minimum, maximum magnitude, number of zero crossings, and number of mean crossings may all be used. In the frequency domain, the peak frequency, peak amplitude, and energy in certain frequency bands may be obtained from a fast Fourier transform (FFT).
- Finally, a pattern recognition algorithm is used to match the measured signal characteristics to the stored characteristics of different combinations of activity types and sensor locations.

Detection of road-induced vibration using accelerometers has also been used to determine whether or not a land vehicle is stationary [21][22], while a calibrated yaw-axis gyro can be used to determine when a vehicle is travelling in a straight line [23].

This paper considers detection of and adaptation to context across a wide range of different application scenarios. Therefore, experiments have been conducted to assess the feasibility of detecting behaviour class from vibration spectra, obtained using inertial sensors. Considering the smartphone navigation scenario presented in Table 2, it would be useful to be able to distinguish a table, a pedestrian and a car. As discussed in Section 3, transitions between vehicle types normally occur when the vehicle is stationary.

Specific force data has therefore been collected using an Xsens MTi-G IMU/GNSS device on a table, a stationary pedestrian, various stationary cars, a moving car and a stationary bus. Note that any accelerometers, including smartphone sensors, are potentially suitable for this. The following processing was applied to enable the measurements to be compared in the frequency domain:

- Take the magnitude of the specific force;
- Subtract the mean of the specific force magnitude to remove most of gravity, which dominates the measurements, to give specific force magnitude residuals from which vibration is easier to identify;
- Apply a discrete Fourier transform (DFT) using the MATLAB function fft. Note that this integrates the specific force magnitude residuals.

Figures 12 and 13 show the spectra of the specific force magnitude residuals for the table and the stationary pedestrian, who held the unit in their right hand. The table data is approximately white, reflecting the noise characteristics of the accelerometers. However, in the pedestrian data, there are peaks in the 6–10 Hz region of the spectrum. This is consistent with the spectrum of the physiological tremor of the hand during isometric muscular contraction, which results from asynchronous discharge of motor nerve fibres [29]. Other possible interpretations include feedback through the peripheral vision system [30]. Thus, vibration at frequencies below 10 Hz can potentially be used to detect the pedestrian behaviour class, whereas a lack of distinct peaks is a signature of the fixed location class.

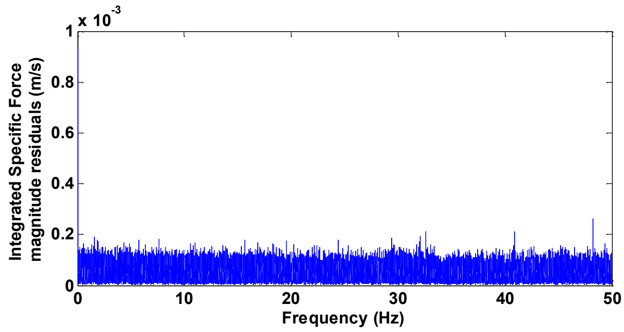

Figure 12: Frequency spectrum of specific force magnitude residuals from an IMU stationary on a table.

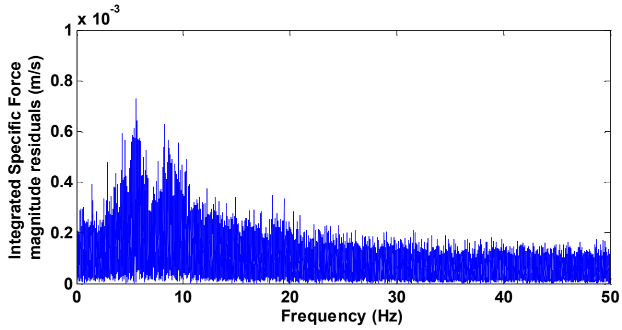

Figure 13: Frequency spectrum of specific force magnitude residuals from an IMU held by a stationary pedestrian.

To test the ability to detect land vehicles, the IMU was placed on the dashboard of a stationary car with the engine turned on. Data was collected for 350 seconds in three different cars: a Ford Fiesta, Toyota Yaris and Nissan Qashqai. Spectra of the specific force magnitude residuals are shown in Figures 14 to 16. Each of the cars shows a different signature. The Yaris has two distinct peaks (17 Hz and 35 Hz), the Qashqai has two peaks at 29 Hz and 35 Hz, the Fiesta has one peak at 43 Hz and a broad region between 32 Hz and 39 Hz with higher than the background levels. Each model of car can be identified by their engine idle vibrations but also there commonalities between the cars. For example, all three of these cars have a peak between 30 and 40 Hz.

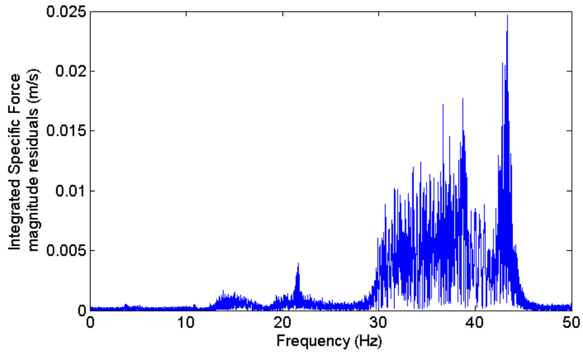

Figure 14: Frequency spectrum of specific force magnitude residuals from an IMU placed on the dashboard of a stationary Ford Fiesta car with the engine on.

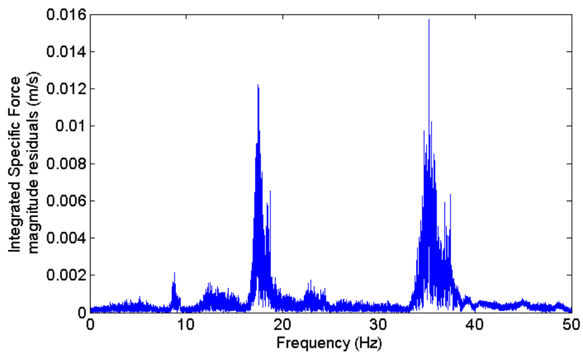

Figure 15: Frequency spectrum of specific force magnitude residuals from an IMU placed on the dashboard of a stationary Toyota Yaris car with the engine on.

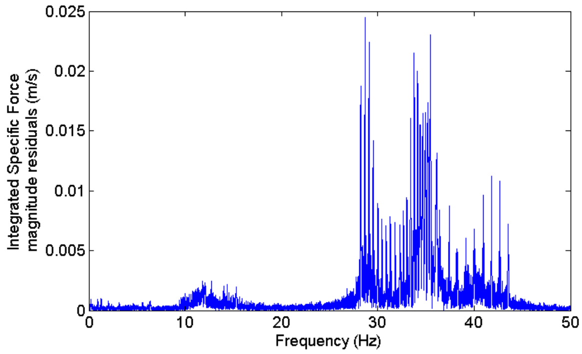

Figure 16: Frequency spectrum of specific force magnitude residuals from an IMU placed on the dashboard of a stationary Nissan Qashqai car with the engine on.

Further data was collected on a Vauxhall Insignia. Here, the IMU was placed on the rear parcel shelf. Figures 17 and 18 show the spectra of the specific force magnitude residuals when the car was stationary and moving at approximately 30 m s^{-1}, respectively. The stationary graph shows a single sharp peak at 28.3 Hz. Comparing this with Figures 14 to 16, it looks like there may be less transmission of engine vibration to the parcel shelf than the dashboard and that the parcel shelf has a resonant frequency at 28.3 Hz whilst once the vehicle is moving, there are three broad peaks at around 4 Hz, 12 Hz and 31 Hz, which are likely to be due to a mixture of both road-induced and engine vibration. This supports [22], which shows that road-induced and engine vibrations are at different frequencies.

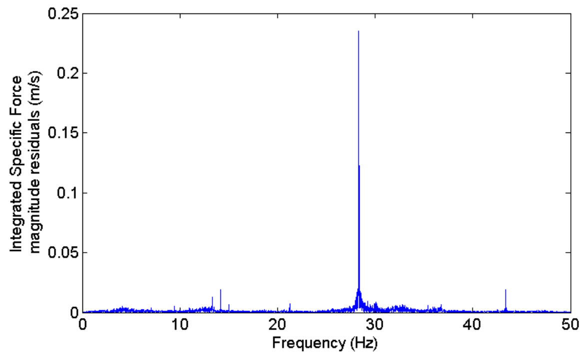

Figure 17: Frequency spectrum of specific force magnitude residuals from an IMU placed on the rear parcel shelf of a stationary Vauxhall Insignia car with the engine on.

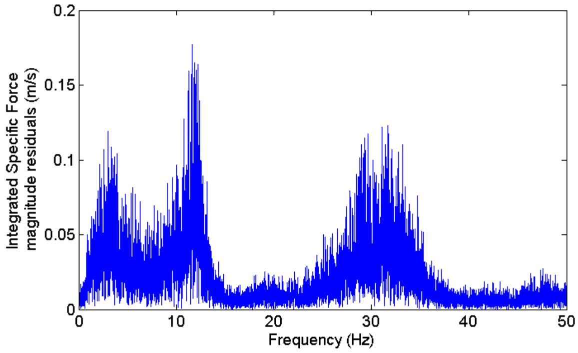

Figure 18: Frequency spectrum of specific force magnitude residuals from an IMU placed on the rear parcel shelf of a Vauxhall Insignia car travelling at approximately 30 m s^{-1}.

Finally, Figure 19 shows the spectra of the specific force magnitude residuals from inside a double-decker bus. The IMU was placed in the middle of the front window ledge, beside the driver's cubicle (lower deck). The engine was at the back of the vehicle. There is a dominant peak at around 24 Hz.

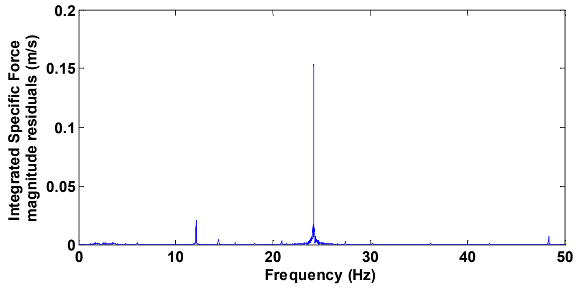

Figure 19: Frequency spectrum of specific force magnitude residuals from an IMU placed in a stationary bus with the engine on.

All of the vehicles tested exhibited one or more peaks between 20 Hz and 40 Hz due to engine vibration and showed little vibration below 10 Hz. This signature can thus be used for context detection, indicating when the navigation system is on board a stationary vehicle powered by a diesel or petrol (gasoline) engine. It is unlikely to work for electric vehicles. The presence or absence or vibration below 10 Hz can then be used to determine whether or not the vehicle is moving.

4.4 Context Determination

Context detection is not a purely deterministic process; it is statistical in nature and makes a number of simplifying assumptions. Therefore, it is prone to error. The reliability of context determination may be improved by

- Using more than one context detection algorithm, where available;
- Considering multiple context hypotheses from each detection algorithm, each allocated a likelihood;
- Weighting each context hypothesis according to its connectivity (Section 3) with the context at the previous epoch;
- Considering multiple hypotheses for the context at the previous epoch, also each allocated a probability;
- Adjusting the weighting of each context hypothesis to account for context association (Section 2.3) and the context requirement specification (Section 2.4).

This may be expressed mathematically as follows. The provisional likelihoods of environmental context category i and behavioural context category j at epoch k, respectively, $\Lambda^i_{pe,k}$ and $\Lambda^j_{pb,k}$, are first computed using

$$\begin{aligned} \Lambda^i_{pe,k} &= \Lambda^i_{de,k} \sum_I c^i_{eI} p^I_{e,k-1} \\ \Lambda^j_{pb,k} &= \Lambda^j_{db,k} \sum_J c^j_{bJ} p^J_{b,k-1} \end{aligned} \qquad (1)$$

where $\Lambda^i_{de,k}$ and $\Lambda^j_{db,k}$ are, respectively, the detected likelihoods of environmental context category i and behavioural context category j at epoch k, comprising weighted averages across multiple detection algorithms where available; $p^I_{e,k-1}$ and $p^J_{b,k-1}$ are, respectively, the probabilities of environmental context category I and behavioural context category J at epoch k–1; c^i_{eI} is the connectivity of environmental context categories i and I; and c^j_{bJ} is the connectivity of behavioural context categories j and J.

Next, the likelihoods are reweighted to account for the requirement specification and the association of the environmental and behavioural context categories. It is assumed that only associated combinations of vehicle type and activity type are considered. The reweighted likelihoods of environmental context category i and behavioural context category j at epoch k, respectively, $\Lambda^i_{re,k}$ and $\Lambda^j_{rb,k}$, are given by

$$\begin{aligned} \Lambda^i_{re,k} &= r^i_e \Lambda^i_{pe,k} \sum_J a_{iJ} \Lambda^J_{pb,k} \\ \Lambda^j_{rb,k} &= r^j_b \Lambda^j_{pb,k} \sum_I a_{Ij} \Lambda^I_{pe,k} \end{aligned} \qquad (2)$$

where a_{ij} is the association probability of environmental context category i with behavioural context category j, r^i_e is the requirements weighting of environmental context category i, r^j_b and is the requirements weighting of behavioural context category j. It may be assumed that requirements weightings are 1 for required context categories, 0 for forbidden categories and some intermediate value for unsupported categories.

The final step is to determine the probabilities of environmental context category i and behavioural context category j at the epoch k, respectively, $p^i_{e,k}$ and $p^j_{b,k}$, using

$$p^i_{e,k} = \frac{\Lambda^i_{re,k}}{\sum_I \Lambda^I_{re,k}} \qquad p^j_{b,k} = \frac{\Lambda^j_{rb,k}}{\sum_J \Lambda^J_{rb,k}}. \qquad (3)$$

If connectivity is expressed using continuously valued transition probabilities, hysteresis can be introduced to the process of switching context by setting the connectivities of all context changes to values less than 1 (assuming that the connectivity of a context to itself is always 1). The connectivity may also be varied as a function of position (e.g. increasing the train-pedestrian connectivity at stations).

In cases where the context determination process does not lead to the identification of a single dominant context category, a context-adaptive navigation system could compute multiple navigation solutions under different context hypotheses. Multiple-hypothesis filtering is discussed in [2].

5. CONCLUSIONS

This paper has laid the foundations for context-adaptive integrated navigation. This enables a navigation system to adapt to different environments and host vehicle behaviour, known collectively as context, to boost accuracy and reliability under challenging conditions. A context-adaptive system detects its operating context and configures its navigation algorithms accordingly.

A five-attribute framework for the categorization of both environmental and behavioural context has been proposed, upon which a standard set of context definitions could be built. This would enable the interoperability of subsystems produced by different organisations.

The concepts of context connectivity, association and scope have been introduced, which may be used to improve the reliability of context determination. Context connectivity is a way of representing the practicality of transitions between different pairs of context categories. Context association provides a way of linking environments to behaviours and vehicles to activities. The scope defines the set of context categories supported by a particular algorithm. It can also be used to specify which context categories a particular navigation system is expected to encounter.

The results of preliminary context detection experiments using GNSS, Wi-Fi and inertial sensors have been presented. It has been shown that GNSS C/N_0 measurements may be used to distinguish indoor from outdoor environments and to distinguish different types of outdoor environment, such as urban and open.

Wi-Fi measurements have been shown to be relatively unreliable for distinguishing indoor from outdoor environments. However, they have been found to be good for distinguishing between different types of outdoor environment. The received signal strength distribution can potentially distinguish urban, suburban and open environments, and the types of access point received can be used to distinguish residential and business districts.

Vibration spectra derived from accelerometer measurements have been shown to be useful for determining when a device is on a table, held by a stationary pedestrian and placed in a stationary car or bus with the engine running. Vibration spectra can also be used to distinguish a moving car from a stationary car.

In addition, a multi-hypothesis approach to context determination has been proposed to improve the robustness of the process.

6. FUTURE WORK

To make context-adaptive navigation a reality, a substantial programme of research and development by the navigation and positioning community is required, including the following tasks:

- The practical demonstration of a basic context-adaptive multisensor integrated navigation system;
- Development of a wide variety of context detection algorithms using a range of different sensors;
- Development of a robust context determination algorithm;
- Development of a wide range of navigation and positioning modules that adopt their configurations and tuning according to the environmental and/or behavioural context.

In addition, a substantial standardization effort is required, comprising:

- The qualitative definition of a set of context categories, based on the framework presented here or otherwise;
- Determination of the association and connectivity of the context categories;
- Development of a standard protocol for communicating context information in navigation systems;
- Quantitative definitions of the standard context categories, following further research.

This could be aligned to the standardization effort proposed for modular multisensor integration proposed in [15].

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