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Localized Processing and Analysis of Accelerometer Data in Detecting Traffic Events and Driver Behaviour

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Abstract: Recent advancements in sensor technologies resulted in the development of sensors with small dimensions and with power consumption that is low enough to be embedded in various mobile devices and which is widely integrated in vehicles. Such sensors can be extensively used to detect real-time traffic events and situations of user/vehicle in context-aware mobile applications. This paper explores the usage of a large number of anonymous mobile devices already involved in the road navigation function as mobile sources of traffic information. Apart from collecting location and speed data, which is extensively used today to calculate average trip time per road segment, we are exploring possibility of using an acceleration sensor integrated with a mobile device in order to efficiently and timely detect critical traffic events and redistribute this information to other drivers through proactive traffic information system. Such a system would be capable of warning drivers of 'near-accident' situations enhancing their situational awareness and general safety.

Keywords: Traffic Information Systems, Extended Floating Car Data, Accelerometer data, Vehicle tracking
Categories: H.1.2, H.3.5, H.4.3

1 Introduction

Recent advances in mobile devices, wireless communications and mobile positioning technologies allow people to use mobile information systems and services at any place and at any time to support their business, touristic and recreational activities. These systems are aware of location, context and situation of mobile users and thus are referred to as location-based and context-aware services. Such services are used in navigation, fleet management, traffic control, emergency management, tourist and business guides, mobile games, etc. Contemporary mobile information systems for traffic and transport monitoring and management are mainly based on static data about road network conditions, road surface status, weather conditions, traffic information, etc. Dynamic traffic information about events that occur in real time, such as traffic congestions, traffic accidents, slippery road, reduced visibility on the road, road works and obstacles on the road, can significantly improve the functionality and usability of these systems. Some sources of this information, such as road works and positions of radar patrols are public organizations and road operators who are responsible for road network management and traffic control. With recent advances of sensor technologies, sensor networks integrated in road infrastructure traditionally represent the significant source of information about traffic events. Although precise and reliable, the main downside of using sensors integrated in the road infrastructure to characterize traffic is economic in nature. A large number of fairly expensive sensors is needed in order to adequately cover extensive road network. An alternative approach is to use a smaller number of mobile sensor nodes that traverse road network with a high enough frequency. Sensors built into the vehicles and sensors attached/integrated to mobile devices used during travel have recently been used as sources of dynamic traffic information [Hauschild, 05]. This data, called Floating Car Data (FCD), if based solely on GPS and eXtended Floating Car Data (XFCD) and other sensors as well, fully describes the movement of a vehicle and its current status and defines the context of the vehicle and the driver [Shaefer, 02].

In order to achieve high reliability of data acquired in such a manner, it is imperative to involve the highest possible number of drivers. Ideally, any driver using mobile device for navigation should be motivated to contribute to a such collaborative navigation system This process should be transparent to end users.

The paper is structured as follows. In the second section we introduce concepts of collaborative driving and extended floating car data (XFCD). This section also presents similar research projects and reviews other approaches to handling extended floating car data. The third section focuses on acceleration sensors and specifics of the data produced by these sensors. The classification of traffic events relevant from the driver's perspective and how these events can be used in collaborative navigation is also presented in this section. The fourth section proposes methods for accelerometer data analysis that can be used to efficiently detect relevant traffic events identified in the previous section while using mobile devices as roaming sensors. The fifth section presents the evaluation of the method over collected data. The final section concludes the paper and present prominent directions for future research.

2 Related Work

Recent market research in the field of mobile devices and intelligent transport systems (ITS) domain [ABI, 10] shows rapid increase in the number of users of mobile navigation devices. It is estimated that the next big step in the development of such systems will be inclusion of location-based and context-aware services. Context in this domain primarily consists of traffic properties (average speeds, congestions) and locations of relevant traffic events and states such as accidents, roadwork, rerouting, etc. Mobile navigation applications have been offering additional traffic information for some time now. Traditionally, sources of traffic information are static sensors built into the traffic infrastructure (road surface, traffic signs) and these sensors typically include inductive loops, infrared sensors and cameras. Road transport systems throughout the world suffer from ever spreading problems of traffic flow congestions and safety. Since individual driver's lack of concentration and situational awareness can be singled out as the most important cause of accidents [European Transport Whitepaper, 11], most of today's driving aid systems target a driver either by trying to increase his situational awareness or by trying to minimize or completely remove the driver's direct influence on vehicle movement. The common approach in such systems is based on data acquired from other traffic participants (drivers or directly vehicles) to influence driver's behaviour or to autonomously influence vehicle's trajectory. The common name for such systems is collaborative driving systems. Research done in [Halle, 05] elaborates this idea by grouping vehicles into platoons, where each platoon includes a leader, manually operated vehicle which guides the platoon of followers on the road. A more moderate approach is to use data acquired from collaborative driving to influence driver's situational awareness while the driver stills remains in full control of the vehicle.

In [Fuchs et al., 07] authors provide a general approach to collaborative driving by defining such systems as context-aware systems in the domain of intelligent transport systems. Context awareness of Driving Assistance Systems (DAS) actually increases driver's situational awareness and can present the driver with warnings and reactions recommendations based on detected traffic conditions in front of the vehicle. This traffic conditions data can be acquired and delivered by vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) collaboration. The authors stress in their paper the importance of propagating data about dangerous driver/vehicle behaviour, warnings about dynamic traffic events, etc. The most important novelty in the proposed approach is the ability to warn drivers about dangerous and near-accident events that are not registered in traditional traffic information systems and which take prolonged periods (couple of months of statistical analysis) in order to identify dangerous places (black spots) on road network.

A lot of work in the field of collaborative driving has been devoted to inter-vehicle communication techniques, ad-hoc routing of messages and ad-hoc network of vehicles (VANET) on the road network. One of such adaptive communication protocols is presented in [Dikaiakos et al, 07]. The authors focus on message routing, caching and delivery in the dynamic network of vehicles communicating using vehicle-to-vehicle communication techniques. More on vehicle-to-infrastructure and inter-vehicle communication can be found in [Keeratiwintakorn et al., 09] and [Daqiang, 2012]. Our approach assumes a centralized navigation service used by numerous traffic participants. The collaborative driving in the form of specialized social networks is not a new concept and there are many commercially available services like Waze [Waze, 11]. It turned out that the most common usage scenario is geotagging of speeding cameras, radars and traffic police patrols. The most important downside of this and all similar systems is the need for manual input of event data. Driver's attention is required during driving in order to report a traffic event and this approach significantly influences safety and actually decreases driver's situational awareness.

Floating Car Data (FCD) approach tries to mitigate this drawback by eliminating a driver from the input loop. FCD represents the concept of collecting, in a centralised location, streams of position and speed data from a group of vehicles traversing road network. The analysis of collected data generates information that characterizes traffic conditions on the covered road network. In practice, this approach has been used so far successfully for detecting traffic congestions. Autonomous traffic data collection is introduced in [Torp, 05]. The authors' aim is to detect queues in traffic with both manual reporting and GPS data analysis. A fleet of taxi vehicles is used as moving sensors. In this work, road network is divided into segments called Report and Measuring stretches, parts of road network, where taxis are expected to drive at full legal speed and not expected to stop for passengers. As shown in their work, this approach scales successfully to large road networks. In order to increase congestion detection reliability the authors combine GPS data with manually identified congestions by the drivers by assigning different weights to manual reports and automatic detection.

Despite being well known for quite some years, the FCD concept is still interesting to researchers as shown in [Thiagarajan et al., 2009]. In this research a traditional FCD concept of streaming positional updates from vehicles to central location is not modified. The authors focus on various locating techniques analyzing their power consumption and accuracy characteristics. For this purpose GPS and WiFi based locating methods were analyzed. Since WiFi (AccessPoint) based locating method is more power efficient than GPS (hereby it is estimated to be 20 times), its inherent lower accuracy is mitigated by using Hidden Markov Model map matching scheme proposed by the authors. Much of the paper is devoted to optimising HMM to produce sequence of traversed road arcs based on inaccurate positional updates. All this is performed at a central location (server side) in order to estimate 'hotspots', road arcs that are congested. This information is further used in routing services.

Typically, a GPS receiver reporting interval is 1 second and this data is sent to the centralized analysis server even more sparsely in order to minimize transmission costs. This data reduction issue is explored in more detail in [Ayala et al., 10]. The question raised is: are we missing some important traffic events that last shorter than this data acquisition interval? What else can be used to characterize traffic in more detail? The Extended Floating Car Data (XFCD) concept involves various sensors available in the vehicle as potential sources of additional information. Common sensors used in XFCD systems include active safety systems like ABS, ESP and windshield wipers activation, head and taillights status, etc. Data from such integrated sensors in addition to positional data streamed to the central location. The work presented in [Masselodi et al., 09] identifies a vastly increased volume of data that has to be transferred when various sensors are included. Therefore, they focus on developing adaptive policy for XFCD data collection. They suggest using temporal, spatial (regional) and on-event modality for triggering sensor data acquisition. The authors suggest that a careful selection of onboard sensors and reporting policy is needed in order to achieve high usability of the system.

Contemporary general purpose mobile devices are more frequently used today for in-vehicle navigation. Almost all of these are equipped with GPS and an acceleration sensor. Many authors suggest that an acceleration sensor alone is enough to detect many rapid traffic events and that it can be used in XFCD systems. Authors of [Mohan et al., 08] propose an innovative usage of accelerometer in their XFCD system. They identify the accelerometer as a 'cheap' sensor in terms of battery and processing power usage. Therefore, the analysis of acceleration data is used to trigger other sensors like a GPS receiver for precise location and audio analysis module for detecting repetitive honking. Honking is considered as an indication of traffic jams in the busy intersections in India. Since the authors' approach implies using a general purpose mobile device that is not permanently installed in the vehicle, they identify important issues of mobile device orientation detection.

An example of using accelerometer as a primary sensor in XFCD system can be found in [Eriksson et al., 08]. The authors' system is based on a fleet of 7 taxi vehicles operating in Boston area. The detection process proposed in this paper firstly requires a manual labeling of the sampled data which is then passed through several filtering stages including low speed rejection, high-pass, z-peak, xy-ratio and speed vs. z-ratio. Low speed rejection removes acceleration peaks induced by opening and closing doors, high-pass filter removes long lasting peaks induced by acceleration and braking, z-peak is the primary characteristic of road anomaly, xy-ratio differentiates between potholes and road-wide anomalies like rail crossings. Finally, speed vs. z-ratio adapts the detection algorithm to the changing speed of the vehicle and alleviates discrepancies when training data was recorded at different speed. Also, clustering by location is proposed in order to further increase detection reliability by eliminating false positives which inevitably occur. This approach successfully removes false positives sourced from inside the vehicle. The approach presented in this paper is specifically tailored for the purpose of detecting potholes (road anomalies affecting only wheels on one side of the vehicle). It is difficult to assess what classes of generalized traffic events can be detected using this approach.

Using accelerometer inside a vehicle with XFCD concept is still a very up-to-date approach as can be seen in [Perttunen et al., 2011]. The authors are still limiting the use of accelerometer data to detection of road surface conditions. An interesting novelty in this paper is classification of road surface condition in micro and macro roughness. The first one describes a type of road surface and can be used to estimate friction between tyres and road surface in order to issue warnings about slippery conditions. The second group represents anomalies which can be manmade or a result of road surface deterioration. The latter two are commonly detected by specialized vehicles equipped with various sensors that periodically traverse road network. XFCD concept recognises regular drivers with accelerometer equipped smartphones as candidates for interesting supplement to these formal detection procedures. In this research, accelerometer data is recorder and post-processed for anomaly detection. The paper does not deal with efficient real-time delivery of accelerometer data to processing centre or power and CPU load requirements of processing techniques. The authors extract several features from recorder accelerometer data: standard deviation, mean, variance, peak-to-peak, signal magnitude area, 3-order autoregressive coefficients, tilt angles and root mean square for each dimension. Since road surface anomalies express periodicity in accelerometer data FFT features were also used. Finally, support vector machine was used to classify and identify types of anomalies in the recorded data.

The traditional Vehicle-2-Vehicle (V2V) communication concept used in many research projects requires complex routing and best-effort delivery protocols. The most notable disadvantage of this approach is that it can not guarantee delivery of messages in ad-hoc VANET if not enough vehicles are available in the area to pass-on the message. This is noted in [Santa and Gomez 2009]. The authors of the paper consider the best-effort delivery approach used in VANETs inappropriate for important traffic warnings and propose a combination of V2V and V2I approaches. This approach effectively eliminates the need for a large number of vehicles participating in such a system in order to route the message in the first place.

In this paper we classify types of driver behaviour and types of general traffic events that are relevant to drivers and explore how they can be effectively detected using various methods of acceleration data analysis. The analysis is localized on general purpose mobile devices used in vehicles. The number of vehicles participating in data acquisition contributes only to road network coverage in certain areas but not the system's capability to proactively deliver notification messages to navigating drivers. Therefore, proactive driving notification system is always capable to deliver notifications acquired from traditional sources like road maintenance or traffic monitoring services even if there are few drivers collaborating and acting as roaming sensors

3 Extended Floating Car Data and Traffic Events Classification

All current navigation systems and services retrieve an ordered sequence of road segments as a result of user's routing request. Apart from the navigation as the main activity, driver's behaviour is influenced by driving environment and context in which he/she moves. Obviously, this includes local traffic regulations and laws, speed limits, etc. This static data is usually distributed with road network maps and is used by navigation services to warn drivers during navigation about traffic rules violations, like speeding. By adding additional data (about speed limits for example) to a simple sequence of road segments we are moving toward contextually enhanced route. On the other hand, traffic is a dynamic system and in order to describe driver's environment in more detail, it is necessary to include dynamic traffic data and attach it to road segments they happened at. The most obvious dynamic traffic data that can be acquired, and that is of interest to the drivers, is traffic flow with congestion locations. Congestions are traditionally detected by counting traffic and measuring average speeds per road segment. This is easily achieved with traditional roadside equipment for traffic counting, such as inductive loops, radar and laser measuring devices and cameras. In order to limit infrastructure costs there are experimental and commercial systems that use traffic participants as probes and that measure their movement either by GPS receivers integrated in mobile devices or by implementation of some other kind of cellular network based locating techniques such as [INRIX]. User's location with speed and course is periodically sent to the central service where it is map matched to a road segment and used to calculate average speeds on this segment as indication of congestion level. This type of dynamic data is finding its way to the users in more recent navigation services that are becoming commercially available. What has not been exploited so far is capability of today's mobile devices used for navigation to detect other classes of traffic events that cannot be detected by mere speed analysis. Today's mobile devices posses plethora of sensors, but we focus on 3D accelerometer and show in this paper that it can be used to effectively detect additional classes of dynamic traffic events that are below spatial and temporal resolution of a GPS sensor which is used in traditional navigation applications. Therefore, our approach does not substitute floating car data concept but actually supplements it, giving it capability to detect and report a wider set of traffic information.

Before trying to further extend the context route it is important to classify traffic events that are important to a typical driver in daily traffic. In order to propose the most efficient detection methods it is important to limit a set of traffic events to the most important ones and analyze characteristics of these events.

We believe the most relevant traffic characteristics and events can be grouped into:

- Traffic and road surface conditions
  - congestions and average speeds
  - road surface conditions and quality
- Dynamic traffic events (near-incidents)
  - sudden braking and acceleration
  - obstacle avoidance
  - lateral skidding
  - abrupt lane changes

All these events exhibit specific patterns in data acquired from accelerometer inside the vehicle.

We can conclude from the previous paragraphs that the temporal aspect, i.e. the duration of the event, is the main characteristic that can be used for classification. Data acquired during longer periods, long enough to traverse whole road segments, can be used to characterize traffic and road surface quality on that road segment. Congestion detection is not the focus of this paper since it is performed efficiently by analyzing the stream of positional and velocity data, calculating short term average speed and comparing it to average speed calculated for road segment being traversed. There are also alternative approaches to detecting congestions by calculating number of start-stop events on road segment. This approach will not be discussed in more detail in this paper since it can be reduced to sudden breaking and acceleration event we identify in the second group of traffic information. Road surface quality and conditions a yet another type of long term traffic information that is somewhat different in nature. This information expresses periodic characteristic and can be detected with frequency analysis of accelerometer data.

The second group can be labelled as dynamic traffic events or near-incident events. Their main characteristic is that they are short-lived and intensive. Therefore, these can be detected by analyzing accelerometer data in time domain. These events include sudden braking and acceleration, obstacle avoidance at both sides, lateral skidding and abrupt lane changes. All these events can also be considered as near-incidents and accident-like , so warning drivers about such events happening in front of them (detected by other vehicles) can significantly increase drivers' situational awareness, and ultimately, general safety.

As noted in the previous section, acceleration sensors are integrated with many general-purpose mobile devices that are used in vehicle navigation today. Acceleration sensor is interesting in our scenario because it represents a perfect supplement to a GPS receiver, being capable of detecting various short lasting traffic events that show typical footprint in accelerometer data. These traffic events include short but violent breaking and acceleration (change of speed) and small but also short and violent changes in vehicle motion direction (changing lanes and obstacle avoidance). GPS receiver with its sampling frequency and precision is unable to detect such fine grained events. Figure 1 shows a typical accelerometer axis orientation also valid for our testbed Android mobile device.

Figure 1: Acceleration sensor axis on testbed mobile device

Security and privacy is another important issue in all massive data acquisition systems that involve personal mobile devices. This issue is particularly emphasised in telematics and location-aware services since these involve individual's whereabouts and routes. Fairly exhaustive overview of privacy and security handling approaches is given in technical report [Cassias and Kun 2007]. The system we propose in this paper is somewhat specific in this sense. As previously stated, data flow in this system consists of two separate and fairly independent processes: On-device localized detection of traffic events and reporting to control centre and redistribution of messages about detected events to other traffic participants. First subsystem, detection and reporting of traffic events do not require user identification and session keeping. Therefore it is inherently anonymous. Delivering notifications and warnings about relevant traffic events to drivers is based on spatial matching of event's location and user's navigation route. Due to this, the system needs to maintain some kind of a link between individual navigation service user (driver) and his/her assigned route. It is convenient that the user identification does not need to be personalised. Furthermore, the session does not have to be maintained across navigation route requests. This results in the possibility to assign the user some impersonalised identification value which is valid only during navigation along the route assigned by the service. Device specific value can be derived for example from the network device MAC address and random portion can be a timestamp of time instance when the routing request was made. Finally, we can apply some sort of irreversible hashing algorithm to these two values to generate a temporary user ID. This approach allows notification delivery to relevant drivers simultaneously preventing anyone to data-mine knowledge about whereabouts of any specific individual.

The scenario addressed in this paper presumes a large number of anonymous users running navigation service on their general purpose mobile devices that are not permanently attached in the vehicle. Different fixing methods mean that device orientation relative to the gravity force vector is not fixed and can differ for specific vehicles (users). Since dynamic traffic events have specific effects on different accelerometer axis, device orientation is an issue that has to be addressed before any acceleration data analysis. This is a separate issue that is not the focus of this paper and it is addresses by other authors, for example in paper [Mohan et al., 08]. We presume that mobile device is oriented as shown in figure 1. If it is not, device orientation has to be taken into account when analyzing accelerometer data. This data has to be 'reoriented' to fit our desired device orientation. Since accelerometer is affected by constant gravity force field, the common approach is to extract gravity force vector and use it to reconstruct the device orientation. In our mobile demo application gravity force vector is extracted using low-pass filter. Furthermore, gravity force is eliminated from real-time accelerometer data in order to isolate only alternating accelerometer data components that are caused by dynamic traffic events we are looking to detect. Graphical output from our demo mobile application is shown in figure 2. Darker colored lines represent gravity force vector components per accelerometer axis (X-red, Y-green, Z-blue). Reconstructed gravity force vector is input into Euler angles reorientation algorithm which modifies accelerometer data in order to 'reorient' it to fit the desired device orientation shown in figure 1.

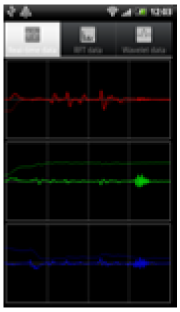


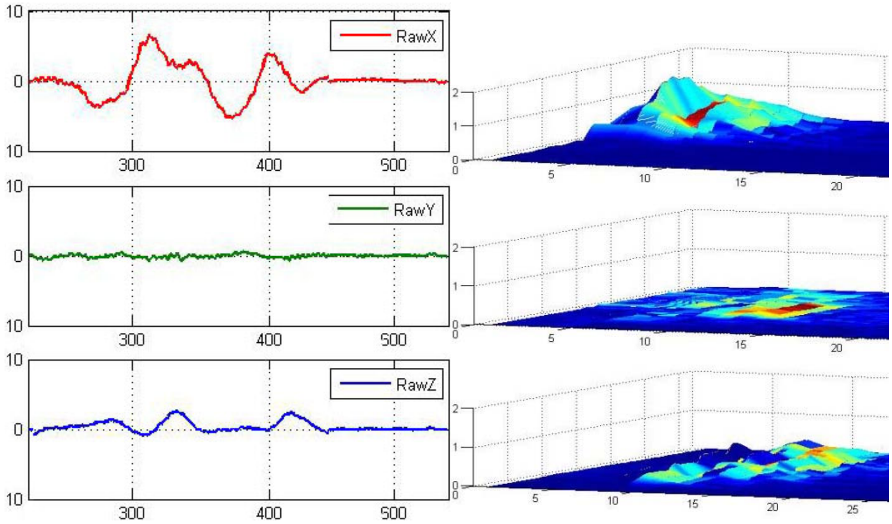
Figure 2: Gravity force filtering on Android demo implementation

During the sample data collection, our demo mobile application collected the accelerometer data with the approximate interval of 20ms between samples. If we agree that the minimum message sent by a mobile device should contain time with millisecond precision, coordinates, speed, course, 3 axis accelerometer data and this information is binary coded, such an average message will be around 50 bytes long. With the aforementioned sampling rate naïve streaming approach would generate around 7MB of traffic per hour which would be unacceptable to any anonymous/accidental user. Even if we reduce the sampling frequency in accordance with Nyquist-Shannon sampling theorem, the volume of the generated traffic would make such a system economically unacceptable to an average navigation user. We have implemented this naïve streaming concept merely for testing and validating purposes. One recorded route with attached accelerometer data is shown in desktop GIS client in figure 3.

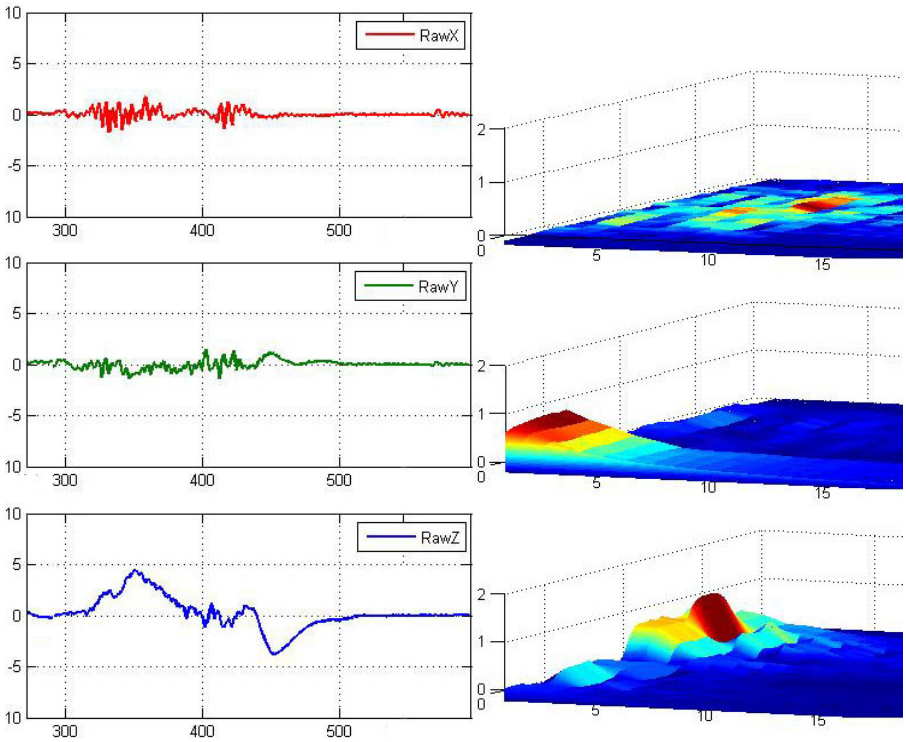
This sheer volume of data makes traditional data streaming from mobile device to central server location used in traditional FCD system virtually impossible. This is recognized as an important downside of FCD concept in terms of scalability and is addressed in [Ayala et al., 10]. The approach used by the authors is to maintain the road network and average speeds model both on server and mobile clients and send updates from the mobile device only when discrepancy to the model is detected. This update triggers the update to the model on both server and mobile client side. The important question is whether it is possible to efficiently create a reference model of a road segment in regard to the accelerometer data. In this paper we focus on a different approach, localized analysis of accelerometer data on mobile devices and sending only notifications about detected events.

Figure 3: Raw accelerometer data streamed to the server

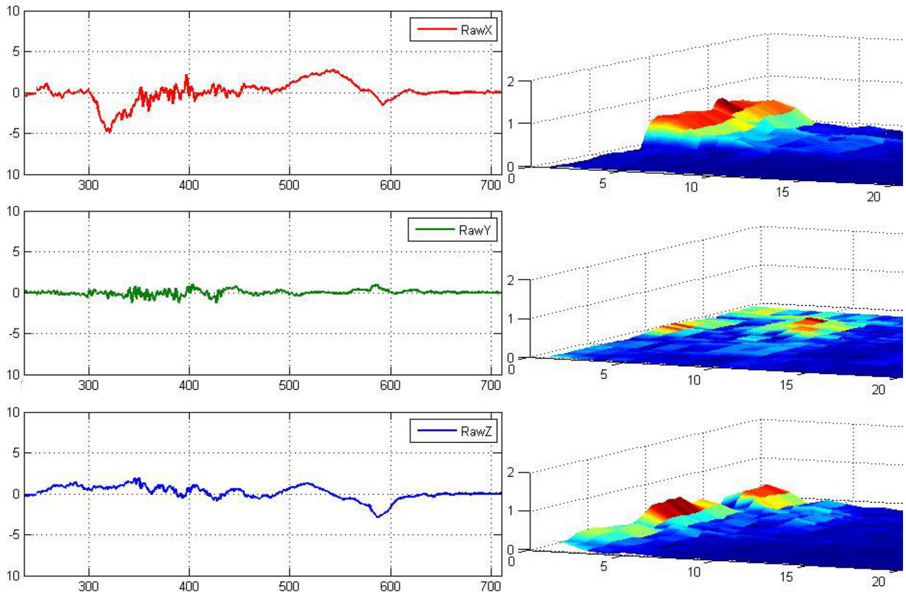
For experimentation purposes we recorded accelerometer data for 5 traffic events we identified as relevant using the implemented Android mobile application running on HTC Desire HD general purpose mobile device mounted in a typical C class car. All events were recorded while the vehicle was moving at 40km/h. The collected data is shown in figure 4 showing all 5 traffic events with raw data and frequency characteristics. X axis for raw data graph is given in samples where there are 50 samples for one second of data. Y axis on the same graph represents acceleration in m/s2. In frequency characteristic graph, X axis shows 26 frequency bins where bin no. 3 represents the 1Hz component. Z axis represents time in number of samples. Some images have been cropped for clarity purposes. The cropping process focused images on important parts of data. One of the most obvious traffic events that can indicate a dangerous situation on the road is obstacle avoidance (shown in figure 4.a). In particular, obstacle avoidance to the left is important for right-hand traffic countries. Obstacle avoidance maneuver starts at approximately sample 250 and lasts for 3 seconds (about 150 samples). This maneuver significantly affects the X axis of the accelerometer. Three smaller peaks on Z axis at positions 200, 320 and 410 represent breaking when front wheels rapidly change direction. Frequency characteristic shows a large value in bin 3 starting at sample 300. This is expected since one half of the maneuver lasts a little longer than 1 second. Obstacle avoidance can actually be seen as two shortly spaced lane changes.



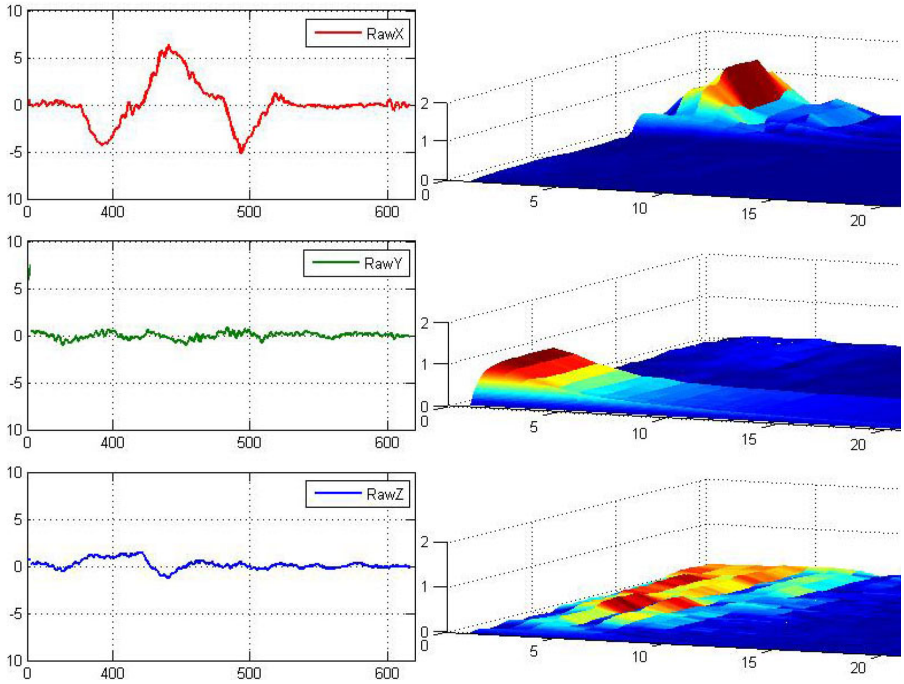
a) Avoiding obstacle to the left



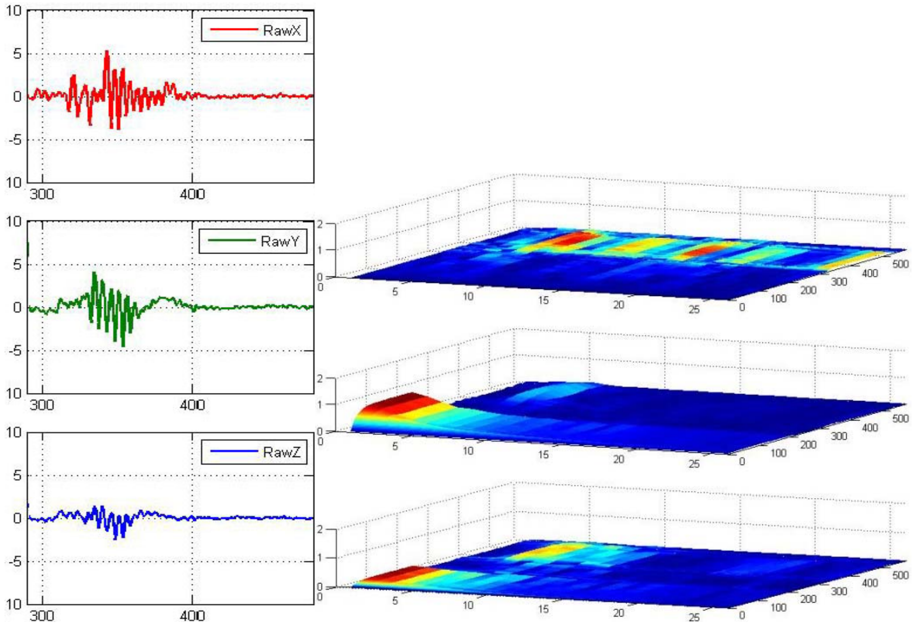
b) Sudden breaking



c) Understeering (skidding) to the left



d) Lane change to the left



e) Running over railroad tracks

Figure 4: Collected accelerometer data for relevant traffic events

Another traffic event that is an indication of dangerous traffic situation is sudden breaking shown in figure 4.b. As expected, this event has a significant influence only on Z axis of the accelerometer. Other two axis show only vibrations caused by violent breaking. It is important to notice here that this event was recorded with an ABS equipped vehicle and breaking continued until the vehicle stopped completely. Event starts at sample 310 and lasts little longer than two seconds. ABS activates at sample 350 when the force exceeds 0.5G. ABS gives distinguishable stepwise decrease of breaking force. Since the vehicle stopped completely, there is a visible snapback at sample 450.

Another event where a driver temporarily loses control of the vehicle is understeering. It is shown in figure 4.c. During this event the front wheels of the test vehicle lose a grip of the road surface. The maneuver started at sample 300 and lasted for two seconds. The front wheels lost grip at 310 at lateral acceleration of 0.5G. There are noticeable lateral vibrations lasting up to sample 500 when the front wheels regain grip.

Violent lane change is not necessarily an indication of a near accident situation but can warn us about bad driving habits. This is shown in figure 4.d. The event starts at approximately sample 380. As previously noted this sample can actually be seen as a half of the obstacle avoidance event.

Finally, road unevenness is represented in our samples set with vehicle running over railroad tracks as shown in figure 4.e. This is the only sample showing higher frequency components in frequency characteristic. The event starts at sample 300 and vibrations last for one second approximately. Since vehicle approached railroad tracks at an angle, equally strong vibrations are recorded on both X and Y axis. Since running over the tracks causes no change in speed, no forces are recorded on Z axis.

More details on the applied analysis algorithms and detection methods will be given in the next section.

4 Localized Analysis of Accelerometer Data

The discussion in the previous section showed the necessity of localized (on-device) analysis of accelerometer data with regard to sheer volume of data generated by typical 3-axis accelerometer. Before deciding on a batch of analysis methods we have identified key events that we believe are relevant in the process of characterizing traffic conditions. Characteristics of the identified events in time and frequency domain were also discussed in the previous section. Common characteristic of all collected and presented samples is that none of these exhibits pronounced periodic characteristic. Frequency domain analysis is a key component in accelerometer data analysis in other domains, such as human posture and activity recognition, and is discussed in more detail in [Kawahara et al., 07]. The lack of periodicity in the collected samples suggests that other analysis methods in time domain are required for efficient detection of relevant traffic events.

It is necessary to start with the calculation of certain statistical values for samples such as the mean value and the variance. They are also used in all other analysis modules. All analysis modules are applied using FIFO buffers maintained for each accelerometer axis. These buffers are 200 samples long (4 seconds). The first section of each buffer (first 50 samples) is labelled as activation buffer (figure 5). One of important questions during the development of mobile based analysis modules is how to limit power consumption in order to conserve battery power and processor occupancy. Since some of the processing involved in the analysis of acceleration data is processor intensive, it is reasonable to activate these blocks only on demand. Therefore, the first phase in acceleration data filtering activates other modules (cross-correlation and DFT). The variance calculation is based on a fairly simple algorithm and is active all the time. This information is attached to speed acquired from GPS. If variance and speed increase over the predefined threshold, the other two analysis blocks are activated and start running in parallel.

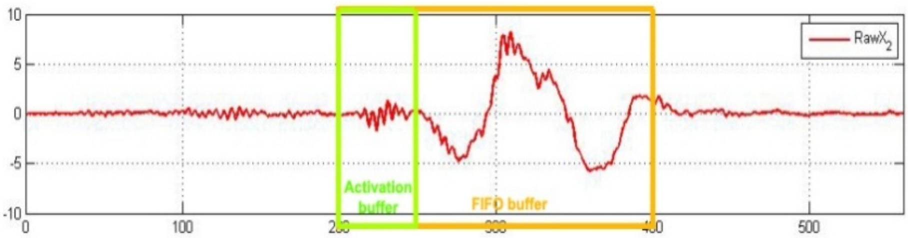


Figure 5: FIFO buffer used for accelerometer data analysis

As previously stated, the main events which need to be detected are not periodic, therefore these events are identified mainly with the time domain analysis module as shown in figure 6.

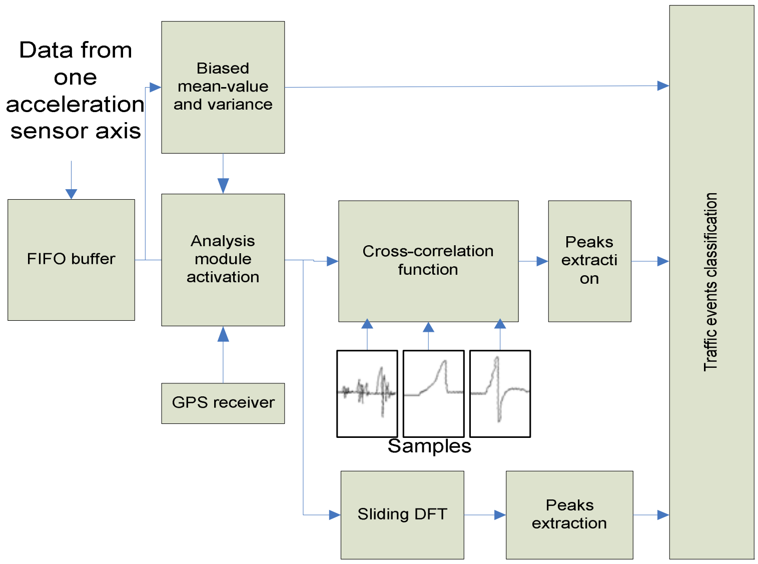


Figure 6: Accelerometer data flow during analysis

This module uses the time characteristic of the predefined samples and performs a cross-correlation calculation with data in the FIFO buffer. In order to provide a baseline for correlation results interpretation, figure 7 shows autocorrelation for X axis of the obstacle avoidance sample.

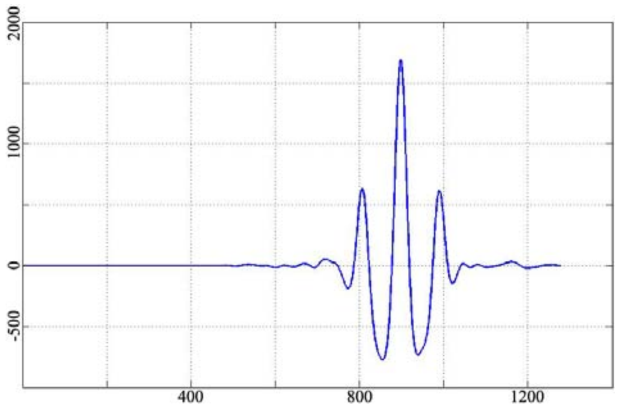


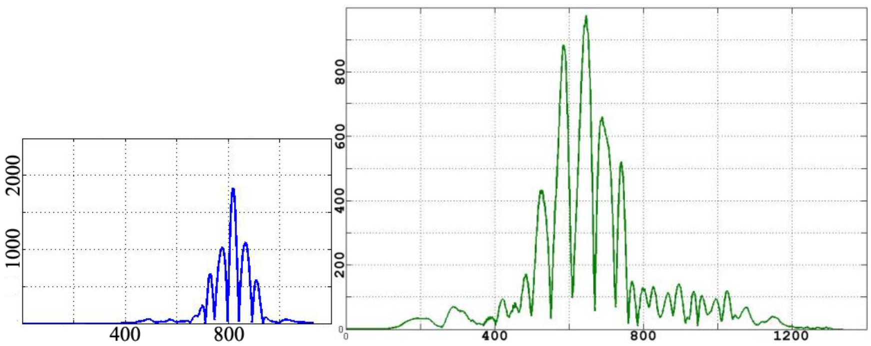
Figure 7: Autocorrelation for X axis of obstacle avoidance sample as baseline for correlation interpretation

The analysis results cannot be interpreted for each accelerometer axis independently. While strong correlation of a sample and real-time signal in one axis can suggest that a certain event may have happened, a different signal signature in other axis and low correlation values for other axis for the same sample indicate that this may be a false positive identification. A good example of such events is running over a pothole with only one side of the vehicle and running over railroad tracks. This is indicated in [Eriksson et. al., 08]. While these two events may be similar if axis are analyzed independently, running over pothole with only one side of the vehicle induces a lateral body roll of the vehicle and a higher amplitude at higher frequencies at both X and Y axis of the accelerometer simultaneously. At the same time running over railroad tracks with both sides of the vehicle simultaneously, induces only strong vertical vibrations of the vehicle. This influences only the Y axis of the accelerometer.

Taking this into account, we calculate the cumulative cross-correlation (CCR) per sample according to the formula:

$$CCR = \sqrt[2]{CR_x^2 + CR_y^2 + CR_z^2}$$

Cross-correlation is calculated per sample for each of the sensor axis (CR_x, CR_y and CR_z) and square mean is calculated as CCR. This method actually takes into account symmetrical characteristic of maneuvers to the left or to the right side. Cumulative cross-correlation of a sample representing obstacle avoidance to the left detected in a longer dataset is shown in figure 8. The figure 8.a shows values of detecting avoiding obstacle to the left sample in maneuver to the same side, while 8.b shows detection in the maneuver to the opposite side (to the right).



a) *b)*

Figure 8: Values of cross-correlation during driving

In contrast, when we try to identify a non-existing sample in a longer dataset we get the calculated CCR values that are an order of magnitude smaller than the established baseline values. Baseline CCR values are shown in figure 7 and figures 8a and 8b. For example, trying to detect violent braking event in a performed obstacle avoidance maneuver, we get distinctly smaller values of cross-correlation as shown in figure 9.

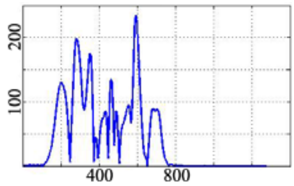


Figure 9: Detection of violent braking in obstacle avoidance maneuver

This pronounced difference in CCR values for positive and negative event detection allows us to set detection threshold value in such a way as to minimize false positives.

Important issue while calculating cross-correlation as a measure of similarity between the prerecorded samples and real-time data is speed of the vehicle when the sample was recorded and the current speed of the vehicle when detection is performed. To take this difference into account, 'shrinking and expanding' the length of the sample is performed while this speed difference is changing. Experimental results of this approach are elaborated in more detail in the evaluation section of this paper.

Although analysis in the time domain is crucial in traffic event detection, spectral analysis is still performed in different data flows as shown in the bottom part of figure 6. Road surface condition and certain events like running over potholes or railroad tracks can be detected in this manner very efficiently since they exhibit distinct higher frequency vibrations. Since the implementation is targeting mobile devices with fairly constraint memory and, more importantly, processing capabilities, performing DFT can prove to be a bottleneck. This is especially important since the analysis module is not the primary task of mobile navigation application and should be transparent to the user. Also, since we are performing real-time frequency analysis while data is collected (passes through FIFO buffer) there is the need to produce values for all spectral bins in DFT algorithm as soon as possible. This constraint is only stressed by the fact that all analysis is always performed threefold, for all 3 axis of the accelerometer. The most suitable approach, applied in our implementation, is using a sliding DFT process which produces output for each input sample. Apart from that characteristic, sliding DFT is algorithmically simpler and more adequate than traditional FFT algorithms in real-time and embedded implementations [Jacobsen, 03]. Another advantage of using this algorithm is that it is possible to calculate an arbitrary number of frequency bins, independently of the number of samples in the buffer. This is especially advantageous in our usage scenario since we do not expect nor are interested in acceleration frequency components higher than 10Hz. Therefore, our setup of the algorithm gives 26 bins with 0.2Hz width for 200 sample FIFO buffer. Frequency domain analysis is used to identify N maximum values in the calculated spectrum (peaks) and compare their intensities and frequencies with the precalculated frequency characteristics for each of the prerecorded traffic events profiles. This filter enables us to identify events whose impact on acceleration sensor has a certain periodicity. A good example of such an event is a vehicle running over road-wide waves created by frequent breaking of heavy vehicles (like in front of the traffic light), certain types of potholes of running over railroad tracks or speed bumps in front of crosswalks.

The output of frequency analysis module implemented in demo mobile application is shown in figure 10.

Figure 10: Output of frequency analysis module

A different impact of the same traffic event on different axis of the acceleration sensor is used to increase event detection precision as it is mentioned in paper [Eriksson et al., 2008]. For that purpose, spectrums calculated for each of the axis cannot be analyzed independently. Time shift of the detected maximum in one axis can decrease detection probability and effectively eliminate incidental match of another maximum in some other axis. Spectrum similarity index (SSI) is calculated by a formula:

$$\frac{1}{SSI} = \sqrt{\sum_{i=1}^{N} (DPBI_i - SPBI_i)^2 \times (DPBA_i - SPBA_i)^2}$$

5 Evaluation and analysis

The important question when extracting knowledge from the crowd is the reliability of the acquired information. We acquire traffic events data from anonymous users driving different cars, using different types of mobile devices for navigation and having different driving habits and styles. Since we try to identify pre-recorded samples of accelerometer data for different classes of relevant traffic events in real-time accelerometer data, it would be unreasonable to have large number of sample variants of each traffic event stored locally on the mobile device for each value of parameters affecting sample characteristics. Therefore, some sort of sample modification during analysis phase is needed and can increase detection reliability.

The speed can be identified as one parameter that is constantly changing during the detection process. Acceleration samples for different traffic events, stored locally on a mobile device, were all recorded at specific speed which is considered typical for each of the events. When these events occur during driving at different speed, an acceleration data characteristic will obviously change. There is a certain threshold of speed difference in which identification is possible. For example, a maneuver for successful obstacle avoidance is not possible and should not be detected at speeds higher then 80km/h. Our sample for this event is, for example, recorded at 40km/h. The difference between a speed at which a sample was recorded and a speed at which a vehicle travels during detection affects both event duration and intensity of forces induced on the vehicle and mobile device. Obviously, maneuvers at higher speeds produce higher intensities of forces and vice versa.

Taking this into account, all samples are modified for their length and intensity according to speed difference before entering the detection module. The length of the sample is changed proportionally to the speed difference and the sample values are interpolated. The intensity of the sample values is again modified proportionally to the speed difference according to the formula:

$$I_{sc} = I_s \cdot K \cdot \left(1 + \frac{V_c - V_s}{V_c}\right)$$

where I_{sc} is the corrected intensity value, I_s is the original intensity value, K is a factor modelling all other differences (type of vehicle for example), V_c is current vehicle speed and V_s is speed at which the sample was taken.

Maximum cross correlation values given by time-domain analysis module as a function of speed difference is given in figure 11. All samples were recorded at 40km/h and, obviously, we have maximum at this speed. Uncorrected values are shown in blue, and corrected values in red.

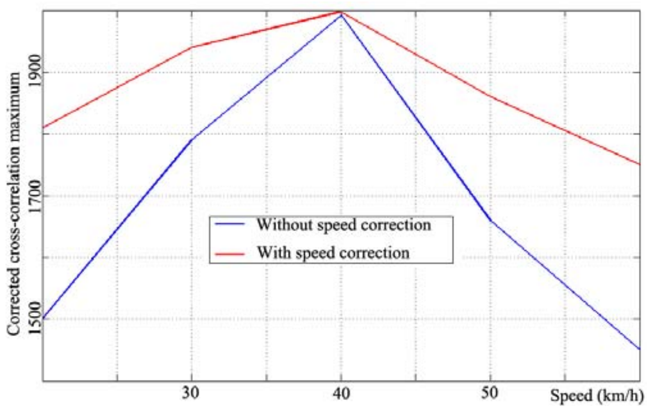


Figure 11: Maximum cross correlation values with (red) and without (blue) speed correction

The other important aspect of our proposed traffic events detection system is its capability to positively differentiate between different types of events, thus eliminating false identifications. Maximum cross correlation values are shown in table 1. when time-domain analysis described in the previous section is applied to sample data for all 5 types of traffic events we have identified as relevant. The table shows distinctly larger values when comparing similar classes of traffic events, therefore allowing us to position detection threshold, for example on a CCR value at/above 900.

	Obstacle avoidance to the left	Obstacle avoidance to the right	Sudden breaking	Lane changing	Understeering (skidding)
Obstacle avoidance to the left	**1880**	-	-	-	-
Obstacle avoidance to the right	998	**1940**	-	-	-
Sudden breaking	244	223	**1910**	-	-
Lane changing	403	465	190	**1790**	-
Understeering (skidding)	298	278	203	214	**1800**

Table 1: Maximum cross correlation values calculated between different traffic event samples taken at the same speed

Given the heterogeneity of vehicles and mobile device types used in our approach false positives are inevitable. An order of magnitude difference between CCR values for true and false traffic events detection suggests that this method can be applied to a wide array of passenger vehicles. To confirm this we have repeated tests for 3 classes of vehicles for each of the relevant traffic events using samples acquired from reference C class car. The results substantiating this assumption are given in table 2.

	Reference C class passenger vehicle	Small SUV	Station wagon family car	Sports coupe car
Obstacle avoidance	2250	1900	1850	2120
Sudden breaking	1980	1660	1910	1880
Lane changing	1680	1230	1325	1790
Understeering (skidding)	2100	1340	1160	2000

Table 2: Maximum cross correlation values calculated between different traffic event samples taken at the same speed

All values in table 2 are significantly above the defined threshold and above the values for false identification shown in figure 9.

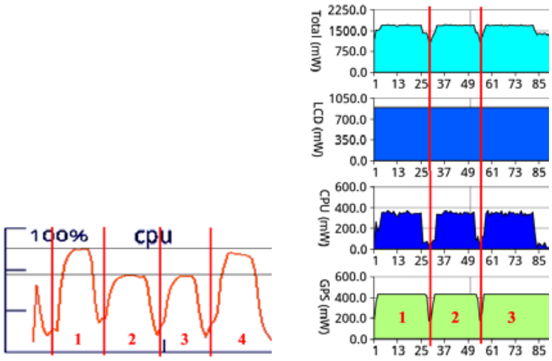
Another, GIS based false positives elimination technique can be applied when traffic events reports are collected on the server side. When a large number of roaming vehicles are operating on a restricted road network and constantly reporting critical traffic events, certain patterns appear when we plot trajectories and events locations in a GIS. As shown in figure 12, similar classes of traffic events are grouped together. We can apply spatial and temporal clustering techniques to estimate reliability of event report and to keep number of false warnings sent to the users to a minimum.

Figure 12: Server-side spatial and temporal clustering performed in order to increase detection reliability

Since we suggest a mobile device based localized analysis and event detection scheme, performance is an important validation factor. As stated in previous sections, accelerometer data analysis and event detection is a background process that should be completely transparent to the end user (driver). The main function of the mobile application is still a visualization of navigation instructions, route and display of notifications and warnings. Therefore, we have performed the analysis of an event detection module with regard to the power consumption and CPU load while running on a mobile device.

Power consumption for different stages of detection is shown in figure 13b. From top to bottom, the graphs represent total power consumption, LCD, CPU and GPS contribution to power consumption. All graphs are divided horizontally into 3 windows labelled 1 through 3. For each of these different accelerometer data analysis modules were tuned on. In window 1 no analysis modules were running. In window 2, spectral analysis (RFT) module was running and in window 3 both RFT and cross-correlation analysis modules were running. Since this was a debug version of the mobile analysis application all calculated values were graphed on a mobile device screen. This visualization was previously shown in figures 2 and 10.

A large LCD display of the used mobile device significantly contributes to the total power consumption. This equals approximately 50% of the total power consumption as seen in the second row graph from the top in figure 13b. GPS was recognized in many other research papers as a power hungry sensor. It contributes to the total power consumption with little more than 25%. This leaves the CPU with a little less than 25% contribution to the total power consumption. The CPU power consumption can be seen in the third graph from the top. It should be noted that two dips in the graph between windows represent periods while we were changing active analysis modules and no detection was performed. Also, disregarding the number and types of active analysis modules, the CPU power consumption seems to be at steady one quarter of total power consumption.



a) *b)*

Figure 13: Mobile device system load while performing event detection

To further investigate this balanced CPU power consumption we looked into CPU load values during the same combination of active analysis modules. CPU load graph is shown in figure 13a. Graph is horizontally divided into 4 windows similarly to figure 13b. During each window different analysis modules were active. During window 1, both RFT and cross-correlation modules were active and cross-correlation was calculated for two samples. In effect, we were trying to identify obstacle avoidance and skidding maneuvers concurrently. During window 2 only RFT was running and during window 3 no analysis was performed, only data visualization. It is apparent from this data that RFT module is very efficient. It insignificantly contributes to the CPU load (difference between windows 2 and 3). Still, besides being very efficient it is not very usable in our scenario since we are not trying to identify periodic events. Also, activation of cross-correlation analysis module adds little less than 25% to CPU load. This is significant, but it is still not overwhelming mobile device. While in window 1 we were trying to identify two events concurrently, in window 4 only obstacle avoidance was being detected. Interestingly enough, additional data samples do not add significantly to the CPU load (difference between windows 1 and 4).

Since real-time visualization of accelerometer data on mobile device was identified as a major CPU load contributor, and it is needed only in the debug period, we have disabled it and used the DDMS (Dalvik Debug Monitor Server) profiling tool to gain further insight in the CPU time distribution of various functions.

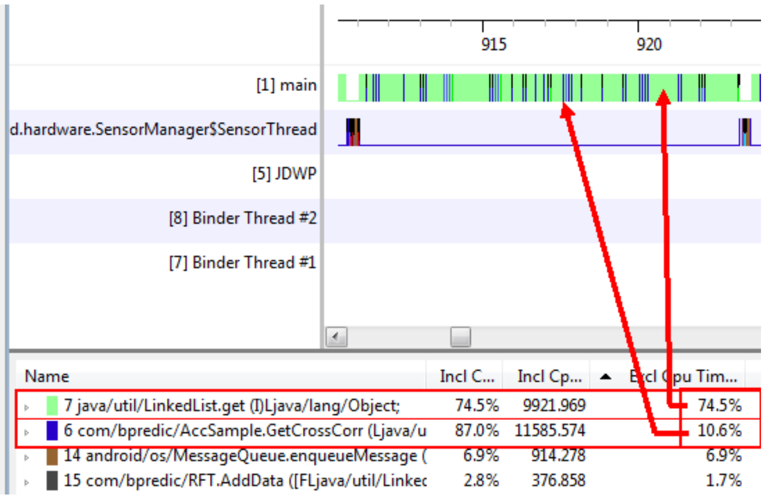


Figure 14: Mobile application profiling results showing functions which are main contributors to CPU load

For clarity reasons we have disabled all debug drawing on device. Profiling results are shown in figure 14. Here we have focused on a period between two samples acquired from the acceleration sensor. Sensor data acquisition activity is visible in the second row from the top labelled *SensorThread*. This period of about 15ms allows us to do data analysis. As can be seen from the figure function *AccSample.GetCrossCorr* takes 10.6% of the CPU time while getting data from the circular buffer is very inefficient and takes 74.5% of the CPU time. Accelerometer data storage and access (light green areas of the timeline in the figure) can obviously be optimized, but an important conclusion from profiling data is that the cross-correlation calculation functions (dark blue vertical lines in the timeline) are efficient enough to be used in real-time, between two accelerometer data samples.

For field testing purposes Android device was used and both acceleration analysis module and proactive navigation notification applications were developed and deployed.

6 Conclusions

Introduction of modern intelligent transport systems assumes a construction of up-to-date road infrastructure and deployment of a large number of expensive sensors. This paper shows an alternative approach in which users, who are most interested in up-to-date traffic information, also act as mobile sensor nodes and sources of information for ITS about dynamic traffic events. Typical mobile phones in use today are equipped with GPS and acceleration sensors needed to detect relevant traffic events mentioned in this paper. Acceleration data analysis algorithms have proven to be efficient enough to run in real-time on such typical mobile platform, widely available today. Additional false positives filtering using spatio-temporal clustering was also proposed. The proposed architecture is centralized with regard to events reports collection and notifications redistribution while event detection is localized on client mobile devices. An alternative approach would be to explore the possibility of an ad-hoc networking and direct communication between vehicles using such a system. This model would require telecommunication technologies which are not typically available on today's mass produced mobile devices.

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