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A Multilevel Traffic Incidents Detection Approach: Identifying Traffic Patterns and Vehicle Behaviours using real-time GPS data

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Abstract—**This paper presents a multilevel approach for detecting traffic incidents causing congestion on major roads. It incorporates algorithms to detect unusual traffic patterns and vehicle behaviours on different road segments by utilising the real-time GPS data obtained from vehicles. The incident detection process involves two phases: 1) Identifies of road segments where abnormal traffic pattern is observed and further divides the 'abnormal segments' into smaller segments in order to isolate the potential incident area; 2) Performs a hierarchical analysis of the vehicles' GPS data, using pre-defined rules to detect any occurrence of abnormal behaviour within the 'abnormal' road section identified in phase 1. The strength of such approach lays in isolating road segments sequentially and then analysing vehicle data specific to the identified road segment. In this way, the processing of vast data is avoided which is an essential requirement for the better performance of such complex systems. The approach is demonstrated using a simulation of motorway segments near Coventry, UK.**

I. Introduction

THE dramatic increase in traffic volumes worldwide is leading to massive congestions causing various social, environmental and economic problems. Congestions are often caused by or made worse by traffic incidents. An incident is "an unexpected event that temporarily disrupts the flow of traffic on a segment of a roadway". Traffic incidents include vehicle collisions, vehicle breakdowns, debris on the road, etc. If such incidents are detected quickly, they can be cleared swiftly, resulting in less congestion. Incidents Detection Systems (IDS) is therefore an area of Intelligent Transportation System (ITS) which have received significant interest see for example [1], [6], [8], [10]-[14]. However, such systems and approaches have to date not completely resolved or dramatically improved the real-time traffic incident detection process. There are various reasons to it including very high cost of implementation, technical complexities and most of all, the disproportionate rise in vehicle numbers as compared to the extent of infrastructural changes.

The success of all the IDS depends on the quality and range of real-time traffic data. The means of gathering data for IDS fall into two categories. The first and most widely utilised involves fixed infrastructure sensors located outside the vehicle such as video recognition devices/cameras, inductive loops, magnetometer, active and passive infrared detectors, passive acoustic detectors, ultrasonic detectors, Doppler and pulsed radar, inductive loop and pulsed laser detectors [2]. The second is based on technology within the vehicles such as airbag activation detection, motion sensors, navigation/GPS receivers and other in-car control devices.

A number of incident detection methods have been developed using different algorithms and technologies for acquiring and processing these real-time traffic data efficiently. Some of these algorithms detect incidents by recognising the effects of incidents on traffic flow. However, the incidents are not detected directly and the geographical extent is limited by the sensors location. Another approach is to detect incidents directly by processing video images. However the geographical extent is again limited by the sensors and cameras location.

In the last few years, satellite navigation systems including in-car GPS receivers are increasing in use in the developed countries. At the same time mobile-phone and wireless technologies have now widespread geographic coverage and can be used to transmit real-time vehicle data to a central location for processing. For instance, vehicle tracking systems involving General Packet Radio System (GPRS), Third Generation (3G) modems or PDA devices, can transmit the vehicle's GPS data to any computer in real-time. This has opened a new dimension in the area of ITS research especially in incident detection and management.

In the United Kingdom, the possibility that road pricing will be introduced has sprouted and feasibility studies have already been carried out by the Department for Transport in the UK [12]. One approach for road pricing is to use real-time GPS data to determine location details of vehicles and to use onboard GPRS/3G based devices for data transmission [12]. Moreover, recent advancements in GPS technology, improved accuracy and reduction of prices brought in-car satellite navigation systems into general use. Following the popularity in add-on satellite navigation systems, car manufacturers are now installing such GPS navigation systems in an increasingly wide range of models. With such market developments and the possibility of government level requirement [12], it is likely that within the next few years most of vehicles in the UK will be equipped with navigation systems and data transmission technologies. Such developments justify the exploitation of GPS technology for IDS.

The IDS approach, presented in this paper, is primarily based on GPS technology and could be used on its own or as a complement to existing incident detection and management systems. It is based on less complex, low cost technologies and uses a multilevel detection approach to avoid processing overheads.

The remainder of this paper is arranged as follows:

Section II reviews the technologies for collecting traffic data for incident detection systems; Section III covers related incident detection algorithms; Section VI describes the architecture of the experimental GPS-based Incident Detection System; Section IV explains the algorithms used in this approach and finally, Section VI assesses the systems performance with various incident scenarios.

II. TECHNOLOGICAL REVIEW

This section describes the issues associated with the data gathering technology for IDS.

A. Fixed Traffic Data Gathering Technologies

Today highway/motorway agencies rely mostly on fixed sensors to provide road usage information and identify traffic incidents. However, fixed sensors do not work optimally across all environmental conditions. Inductive loops and magnetometers exhibit the best range of operating conditions, working equally well by day and night and across most weather conditions. Inductive loops and magnetometers however have poor performance in snow conditions [2]. By contrast passive acoustic sensors work well under any snow condition, but have a more limited range of operating conditions and require clear days and nights [2]. Installing and managing these technologies on a wider scale is considered to be a very complex and expensive approach [5].

B. Global Positioning System (GPS)

Differential GPS (DGPS) and Wide-Area Augmentation System (WAAS) enabled standard GPS receivers provides accuracy about 1 to 2 meters [5], [5]. Most of the GPS receivers can relay position data to a PC or other device using the National Marine Electronics Association (NMEA) 0183 and 2000 protocols. These protocols are used by Automotive Navigation and tracking systems in order to determine the vehicle information from GPS signals such as: Coordinates (longitude, latitude, altitude), Time, direction, speed, and GPS fix quality (0=no fix, 1=only GPS or weak fix, 2=DGPS strong fix).

The GPS data provides sufficient information for identifying general traffic patterns such as the average speed on a specified road and to identify abnormal behaviour of a vehicle like unusual deceleration or change in direction. Such real-time information may be able to infer the occurrence of an accident.

Having reviewed the different means to collect information for IDS, the next section will review current algorithms for IDS and present the new GPS approach.

III. INCIDENT DETECTION METHODS

The first part of this section aims to identify an appropriate algorithm for GPS based IDS. Current incident detection algorithms have been classified in four major categories: prediction algorithms, model-based identification algorithms, methods based on a traffic flow model and computational intelligence [5].

In model based detection algorithms, traffic flow models are derived and validated using historical records. These models are usually non-linear and operate at the macroscopic level. They can be implemented from past traffic information, using dynamic state space techniques to estimate the state of the traffic (in terms of density and flow) as well as perform additional observations such as on-ramp entrances to a particular road or segment length and capacity. These models can then be exploited, to predict the evolution of traffic pattern. If the traffic differs significantly, then it may be that an incident has occurred. A standard alternative to model complex non-linear behaviour is neural networks (NN). NN can be trained on past data to recognise traffic flow patterns and so recognise states associated with the presence or absence of incidents [1],[14]. Whilst effective, NN approach can be difficult to train and convergence to a solution can be slow. Understanding what a NN model means is difficult and a large amount of historical data are required for training purposes. Fuzzy logic has been used to overcome issues associated with scarce data and capture knowledge based on expert experience. Fuzzy algorithms have used the idea of a fuzzy boundary and the change in occupancy or relationship between speed and density between neighbouring detector stations to identify traffic incidents.

At the micro or local level, image-based algorithms have been used to detect and verify incidents from image sequences [1]. Another approach is the use of probe vehicles. There are three kinds of data that have been used for probe vehicles, GPS data [1], [3], [5] electronic toll collection tags [6] and automatic number-plate recognition [7]. In these approaches the time to travel along a section or road is monitored. Statistical methods, based on historical data, are used to detect anomalously long travel times.

In traffic pattern recognition algorithms, the aim is to recognize and discriminate between different traffic patterns using data from detector stations for example, monitoring the upstream and downstream occupancy using loop detector stations on a freeway or motorway [1]. The expected state is when occupancy increases upstream, but decreases downstream. An incident is detected when upstream and downstream occupancy passes predefined thresholds. Prediction algorithms are usually applied in situations where traffic forecasting is required. Historical traffic data is used to analyze the traffic-flow parameters using statistical forecasting techniques and compares the predictions to the actual flow to identify incidents [5]. In this approach, the detection algorithms are both prediction and method based.

Instead of totally relying on fixed data gathering technologies, this research focuses on real-time GPS data collected directly from the vehicle. This makes possible to avoid the complexities of infrastructural changes as well as the ability to be incorporated with any other incident

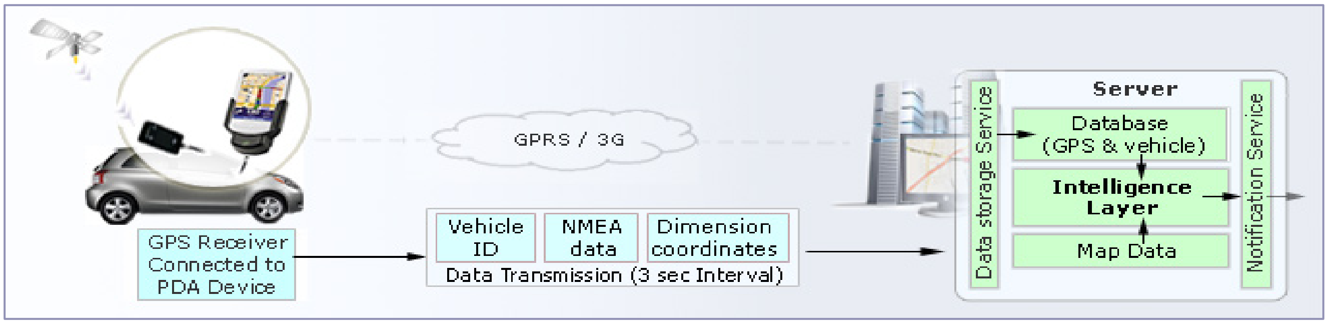

Fig. 1. System Architecture

management system already in place. However, this approach is dependent on the quality of traffic data, hardware performance and intelligent integration with map data.

A. *Incident Definition*

Identifying traffic pattern is quite difficult, identifying individual vehicle behaviour is even more difficult, as it involves analysing factors such as vehicle type, timing, speed, road type, location, conditions and driver details [9]. The traffic pattern is a cumulative behaviour of vehicles, such as their number or the average speed of vehicles on certain road sections. Abnormal vehicle behaviour is often an incident of the following types:

Vehicle-Vehicle Collisions:

- Rear-end collision, Head-on collision
- T-bone collision, Side-swipe collision
- Glancing collision, Multiple vehicle collisions

Vehicle-Object Collisions:

- Vehicle collides with a road-side object, such as a pole, pillar, crash barrier, or tree.

Other Incidents:

- Breakdowns, spun vehicle either at the side or in the middle of the road causing congestion

IV. GPS-Based IDS Implementation

This section describes the details of the Incident Detection System implemented to analyse and validate the new multilevel detection approach. The system consists of several hardware and software components.

1) *Vehicle-based Mobile Client:*

- Personal Digital Assistants (PDA) running Microsoft Windows Mobile 5 PPC Operating System, with GPRS connectivity.
- GPS receivers with WAAS and DGPS support.
- PDA software application performs:

  a) Converts GPS signals into coordinates, speed and direction using NMEA protocols (in WGS-84 format);

  b) Calculate the vehicle's coordinates, including its bounding box;

  c) Optimise/bundle relevant GPS data and trigger emergency events to server;

  d) Transmit vehicles data (coordinates bundle, vehicle ID, and timestamp) to the server at every 3 second interval.

2) *Gateway Server:*

- Microsoft Windows Server 2003 system with a static IP address for storing and processing the vehicle's GPS data.
- Microsoft SQL Server 2005 database for storing vehicles GPS data and road segmentation details.
- Microsoft Virtual Earth based visualisation and map information.
- Web services layers 1) Clients interface for data collection and storage 2) Notification interface for external systems
- Intelligence Layer application, which includes a detection algorithms (described in Section V) and communicates with Microsoft Virtual Earth SDK and the database

The intelligence layer is a separate C# application incorporating all the incident detection steps (described in section V). It sends relevant data to the "notification web service" when the system detects any abnormal traffic patterns/incident. Finally, the Microsoft Virtual Earth is used to display the real-time traffic data and abnormal behaviours.

V. GPS-Based Incident Detection Approach

This section outlines the method used in the intelligence layer application for detecting the location of traffic incidents causing congestion. It is assume that each vehicle on the monitored road is equipped with GPS receiver and data transmission device for example GPRS enable mobile device. The GPS data from all the vehicles is transmitted to the server in real-time. The incident detection process involves two phases:

Phase 1: Analysing Traffic Pattern

To analyse the traffic patterns more efficiently, the roads are dynamically divided into smaller segments. The length of these segments depends on the type of road, date, time and weather conditions. After the segmentation each road segment is assigned a normal average speed range for example, 500 meters segments for a motorway type on weekday's peek time with normal average speed between 50-70 mph under normal weather conditions.

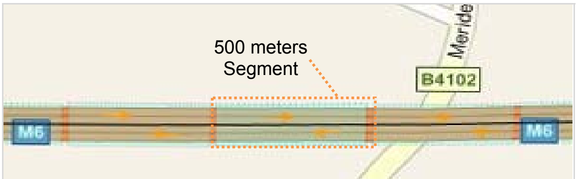

Fig. 2. Motorway segments and streams

The boundary of a segment is represented as geo-fence which is the set of coordinates creating a polygonal layer around the road segment. Each segment has upstream and downstream representing the flow of the vehicles. The vehicles' current location (coordinates) appearing within the segment boundary (Geo-Fence) determines the segment within which they are currently positioned. Phase 1 consists of the following steps:

Step 1.1: Segment the road dynamically and assign normal average speed.

Step 1.2: Calculate in each segment the average speed of vehicles going in a certain direction.

Step 1.3: Compare current average speed with the normal average speed for the segment. If the average speed for the segment is significantly slower than normal average speed then that segment is marked for further analysis and step 1.4 applies.

Step 1.4: Identify road segment with the lowest average speed and apply next step.

Step 1.5: Compare the average speed of the vehicles in the neighbouring road segments with that of the marked segment.

Step 1.6: Determine the current average speed of the road segments in front and behind of the marked segment, see Figure 3. If the average speed in the 'front' segment is much higher than the 'marked' segment then a blockage within the slowest is likely. Since there are possibilities, that segments could include normal stoppage points such as traffic lights, roundabouts and junctions, it is assumed, that up to date map data is also incorporated, to distinguish between normal and abnormal stoppage points.

Step 1.7: Divide the marked segment in Step 1.4 in 10 smaller sub-segments and repeat the steps 1.2 to 1.6 this time for each sub-segment.

In Step 1.5, the average speed in segments in front and behind the marked segment is found in order to detect if there is an incident in the slowest marked segment or there is just a general congestion. If there is just a general congestion, the average speed will be similar in adjoining segments. However, if there is an incident causing a blockage in the marked segment then the average speed of the segments in front of that blocked/marked segment will be higher and with less number of vehicles.

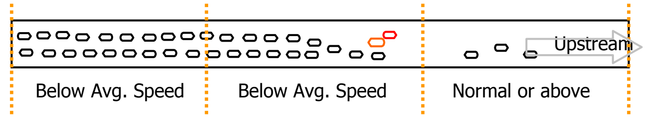

Fig. 3. Segment causing congestion

If the identified sub-segment of the road still shows the bottleneck situation illustrated above after certain time (based on type of the road and conditions), then Phase 2 steps will be applied. The Phase 2 analyses the GPS data of the individual vehicles in order to identify any abnormal vehicle behaviour.

TABLE I
PHASE 1 ALGORITHM

Analyse traffic patterns on road *R*

1: Start *Segmentation process* (R, Type, Boundary coordinates)
  Switch *Conditions* (Time, Date and Weather)
    // cases predefined
  Return *Segments details*
    //Segment_Length, boundary coordinates, Normal_Avg_Speed
  Classify upstream || downstream

2: For Each *Segment (or sub-segments)* S *in* R
  Calculate $$Current\_Avg\_Speed(S) = \frac{1}{N}\sum_{k=0}^{N} vehicle\_Speed(S)$$
    // where N–*number of cars in segment* S
3: IF Current_Avg_Speed (S) << Normal_Avg_Speed (S)
  Mark Segment *S*;
4: Do While *Segment* S *with lowest* Current_Avg_Speed *is identified*

5: While Current_Avg_Speed (S) ≥ Current_Avg_Speed (S±1)
  S=*S* ±1;
  Else Process Segment S;

6: Get Current_Avg_Speed (S ±1)
  IF (Current_Avg_Speed (S +1*)* >> Current_Avg_Speed (S))
    && (Normal_stoppage_pts (S) == 0)
  Mark *Segment* S *as possible incident location*

7: Start *Sub-Segmentation process* (S, Boundary coordinates)
  Segment_Length = Segment_Length / 10;
  Repeat *Step 2 to 6* // for all the sub-segments

8: Wait *for interval* T
  IF *no change in* Current_Avg_Speed (S)
  Execute *Phase 2 on* S

Phase 2: Identifying Vehicle Behaviour

The GPS data of the vehicles within the identified sub-segment in phase 1 are analysed in the following steps to identify behaviour of individual vehicle and to examine if an incident may have occurred.

Step 2.1: Identify the vehicle(s) which have:

- Significantly lower speed than the current average on particular sub-segment
- Completely stopped
- Heading in a direction different to the traffic flow

Step 2.2: Determine from the map data if the segment consists of or is close to a place, where vehicles usually stops *e.g.* traffic lights, junction or level crossing. If it is, then go to step 2.3, if not go to step 2.4.

Step 2.3: To enable short or temporary blockages to resolve themselves, pause for a time based on the location *e.g.* for traffic lights wait for 1 minute, for level crossing wait for 5 minutes. If the condition(s) identified in step 2.1 still exist go to step 2.4.

Step 2.4: Analyze the GPS data to determine if:

- All current vehicles' average speed within the segment became significantly lower than the average speed.
- Vehicle(s) stopped abnormally by analysing their velocities over time (e.g. a vehicle decelerating from 70mph to 5mph in 2-3 seconds on a motorway).
- The coordinates of a corner of a vehicle are less than 2m from the bounding box of another vehicle and if the two vehicles are separated from each other by less than 5m in height. (It is to avoid level issues such as an overhead bridge with same flow of vehicle direction).

Step 2.5: Pause for a certain time (based on type of road and condition) to check if any change in average speed occurs, if not the system triggers an alarm (notifies the notification service) with the concerning vehicles and the exact incident location of the sub-segment.

TABLE II
PHASE 2 ALGORITHM

```
Identify vehicle behaviour in sub-segment S

1: For 1:N   // N = number of cars
     IF Speed (N) << Normal_average_speed   || Speed (N) ≤ 0
        || Direction (N) not within the normal range of the flow
        Mark Vehicle_N

2: IF ( Normal_stoppage_pts  (S) == 0)
      Goto 3 Else Goto 4

3: Wait for interval T1
      IF  no change Goto 4

4: For Each Vehicle_N in S
     Analyse GPS Data (Vehicle_N)
      // abnormal deceleration,  direction change, collision etc. (See 2.4)

5: Wait for interval T2
      IF  no change
     Alert and return (Location coordinates, Vehicles_List)
```

VI. PERFORMANCE EVALUATION

This section evaluates the performance of the incident detection system in terms of Detection Rate (DR), False Alarm Rate (FAR) and Mean Time-To-Detect (MTTD). The system was evaluated using the combination of real and simulated data primarily on less complicated road sections with no normal stoppage points. Vehicles equipped with GPS receiver attached to PDA devices were used to send the real GPS data to the gateway server. The test vehicles crossed the examined road section in different combination i.e. within normal average speed range, lower speed and stopped temporarily (on the hard shoulder lane). As it is not possible to equip all the vehicles crossing the examined section with GPS data transmission devices therefore the GPS data from the test vehicles was altered and replicated by using GPS simulator program in various ways to include a variety of normal and abnormal traffic situations. The system was then examined by processing the large volume of GPS data representing various normal traffic scenarios and incidents such as vehicle(s) stopped in middle of the road, vehicles decelerating abnormally, collisions, temporary blockages/congestions including vehicles losing the GPS signal on a specified motorway section of 10 miles. The section was divided in 10 and then in 20 segments. The number of vehicles at any given time was different with maximum up to 200 per segments.

The DR for phase 1 was relatively consistent, however as the number of vehicles increased the DR dropped as well. This is primarily due to the coordinates bundling method used in the mobile client. The DR recorded for Phase 2 was lower than phase 1 as it deals with very complex data and currently the threshold for detection alarms is quite low in order to keep the FAR as lower as possible.

TABLE III
DETECTION RATE (DR)

Phase	Vehicles Per Seg. *(on different time interval)*	Seg.	Road Type	DR % *(Average)*
1	10 - 20	10	Motorway	78.70
1	20 - 80	10	Motorway	75.30
1	100 -200	10	Motorway	71
1	100 -200	20	Motorway	71.60
2	10 - 20	10	Motorway	62.70
2	20 - 80	10	Motorway	59.30
2	100 -200	10	Motorway	53.60
2	100 -200	20	Motorway	52.20

DR = Detected accidents divided by actual accidents

TABLE IV
FALSE ALARM RATE (FAR)

Phase	Vehicles Per Seg.	Segments	Road Type	FAR %
1	10 - 20	10	Motorway	1.18
1	20 - 80	10	Motorway	1.23
1	100 - 200	10	Motorway	1.37
1	100 - 200	20	Motorway	1.38
2	10 - 20	10	Motorway	2.16
2	20 - 80	10	Motorway	2.28
2	100 - 200	10	Motorway	2.31
2	100 - 200	20	Motorway	2.32

FAR = Number of incident free interval with false incidents alarms divided by the total number of incident free intervals

As there were no normal stoppage points in the evaluated road section therefore the wait interval in step 2.2 is not included in the results. The MTTD will be different for different road types and conditions due to step 2.5 wait interval. For the purpose of simulation it was set to 3 minutes for motorway.

TABLE V
MEAN TIME-TO-DETECT (MTTD)

Phase	Vehicles Per Seg.	Segments	Road Type	Avg. MTTD *(hh:mm:ss:ms)*
1	10 - 20	10	Motorway	00:00:2:20
1	20 – 80	10	Motorway	00:00:2:20
1	100- 200	10	Motorway	00:00:2:20
1	100 - 200	20	Motorway	00:00:2:30
2	10 - 20	10	Motorway	00:03:3:40
2	20 – 80	10	Motorway	00:03:3:40
2	100- 200	10	Motorway	00:03:3:40
2	100 - 200	20	Motorway	00:03:3:50

MTTD = Difference between the time of accident occurrence and the time of accident detected

Fig. 4 (a). IDS interface showing segments (geo-fenced) with status. Darker colour segment (or sub-segment) represents segment marked in phase 1 and to be processed in phase 2. Fig. 4 (b). Sub-Segment with no problems. Fig. 4 (c). Yellow colour vehicle represents vehicles in congested segment while the red colour shows the vehicles are identified as causing incident.

VII. Problems and Complexities

- The dynamic segmentation depends on the accuracy of polygonal coordinates lines provided to the system. In case of complex road section geometry, the segmentation requires close points of coordinate's line for accurate geo-fencing.
- Microsoft Virtual Earth SDK does not provide stoppage point level querying for the UK. The simulation results are, however, likely to be affected after integrating the virtual earth map data querying once available.
- The accuracy range of GPS makes it difficult to distinguish between vehicles collision and vehicles stopped close to each other due to congestion, traffic lights, junctions, crossings, roundabouts etc. The system currently waits for certain time and if the problem remains, then only the incident is alarmed. However this wait affects the MTTD results.
- GPRS data is not always accurate and disconnection is common. This is the major drawback of the system implementation however it does not affect the performance of phase 1 as any vehicle sending correct data could still be used as probing vehicle to identify the congested sub-segment. However, phase 2 requires the data to be more accurate for higher detection rate.

VIII. Conclusions and Further Work

This paper presented a new GPS based incident detection approach, combining dynamic road segmentation logic with the individual vehicle behaviour identification methods. The system was assessed using a simulation system implemented using the components likely to be used in the final product. The visualisation of the simulation has been realised with Virtual Earth. The preliminary results presented in section VI shows promising results for M6 motorway segments in the UK. The next stage of this research will evaluate the approach using real-time data obtained from test vehicles on several roads around Coventry city, UK. It is also intended to broaden the scope of this research by including additional in-car sensor technologies such as airbags triggers and enhancing the mobile application to enable distributed processing and in-car decision making. This also includes real-time communication between the server and mobile applications so the vehicles heading towards the congested parts of the roads could be alarmed in advance by the server.

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