A Collaborative Framework for Traffic Information in Vehicular Adhoc Network Applications

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Abstract

The rise in vehicular traffic in city roads and availability of limited resources to regulate and control them are major challenges in real time traffic monitoring. The advance, evolving and best solution in Intelligent Transportation Systems (ITS) to such challenges are the traffic management application of Vehicular Adhoc Network (VANET). The application requires several information related to vehicular traffic or safety measures such as speed, traffic density, parking details etc., transmitted across the co-operative vehicles of VANET. This information can also be enumerated from different sources to ensure the backup or assurance of availability of information to improve the precision of the application. This paper proposes a Traffic Information from Collaborative Framework (TICF) that uses a novel Spatial Traffic Video Content Processing (STVCP) architecture for a VANET based application. TICF ensures the concurrent availability of information to VANET application from the most significant computer vision based infrastructure using STVCP through Common Object Request Broker Architecture (CORBA). The performance of the proposed architecture and framework are tested and analysed with simulated values of co-operative vehicles and real time traffic videos for information. The results show an improved performance of VANET application without loss of any valuable information.

Keywords: Intelligent Transportation Systems, VANET, Common Object Request Broker Architecture, Computer Vision Technologies, Traffic Management Applications.

1 Introduction

The traditional Intelligent Transportation Systems (ITS) based solutions for effective traffic monitoring is expensive in nature as the installation of its components comes with a huge cost. Different countries have developed different strategies and techniques based on their socio-economic background, geographic locations and environmental conditions to implement ITS. The basic idea of an ITS is to initially collect data through various sensors or other acquisition technology. The collected data are analysed and combined with operational and control concepts that are integrated with various components to provide an interrelated systems that support and provide solution to transportation problems [15]. When these interrelated systems that provide information are adopted into technologies and services such as vehicles, infrastructure and traffic management, it provides drastic improvement to the safety and efficient mobility of travellers. This improvement and innovation based system of ITS has been implemented in various parts of the world including USA, Japan, Middle East, Canada, European nations etc.[10].

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The latest and advanced approach involves cutting edge technologies like smart phones, GPS based solutions and information sharing among vehicles using optimally placed road side infrastructure in a road segments. Vehicular Adhoc Network (VANET) Infrastructure supports these components for effective traffic monitoring. The usage of these recent technologies facilitates accurate and faster information sharing. VANET infrastructure is becoming the advanced technology to improve driving experience efficiently. All future vehicles will be embedded with advance technologies that ensure safety and comfort [3]. A plenty of real time service applications related to safety, commercial, convenience and productive are available from this technology [6]. However, the ability to share traffic information is restricted to the mobile vehicles that support these technologies. Availability of information round the clock and scalability are therefore limited with VANET as there is a huge dependency on high end mobile vehicles. These limitations does not suffice the traffic management solution to be efficient and effective [21]. To handle these short comings, this paper proposes a Traffic Information from Collaborative Framework (TICF) that uses a novel Spatial Traffic Video Content Processing (STVCP) architecture for traffic management based VANET applications. The proposed TICF for VANET collaborates with computer vision infrastructure via Common Object Request Broker Architecture (CORBA) to ensure open exchange of traffic information for VANET based application such as Traffic Congestion (TraCo) estimation. The traffic information from computer vision infrastructure are extracted using proposed STVCP and conversed to CORBA. STVCP presents a novel algorithm that uses an efficient Background subtraction (BS) technique by utilizing Hue, Saturation and Value (HSV) color model for processing real time video from surveillance camera to obtain the traffic information.

The remainder of the paper is organized as follows: Section 2 discusses the existing works related to the proposed architecture. Section 3 presents a brief introduction to VANET, its applications and challenges. In Section 4, the detail of the proposed work that includes Traffic Information from Collaborative Framework (TICF), its ontology and Spatial Traffic Video Content Processing (STVCP) architecture is presented. The results and performance analysis of the proposed frameworks are presented in Section 5. Section 6 includes the conclusion followed by Acknowledgment and References.

2 Related Works

ITS service application is dependent on real-time accurate traffic information. Traffic information such as speed, volume, density, headway, etc., are obtained as processed information from several sources such as Global Positioning System (GPS), bluetooth, traffic videos, LIDAR, RFID, On Board Units (OBU), traffic videos, etc. [15]. Among these sources, traffic information from co-operative vehicles of VANET is the most recent and popular technique. However, VANET-based solutions have challenges such as collecting and transferring data safely, sensor integration, overhead issues during rise in number of vehicles, packet loss, etc. There are numerous works related to improving the communication of traffic information in VANET over the past decade. The wireless communication of traffic information by travellers raises significant security and privacy issues that cannot be neglected. Large number of threats in confidentiality, integrity, authentication, identification and availability of information are defined in VANET [2]. There are several attacks such as eavesdropping, denial of service, routing attack, revealing identity, GPS Spoofing, Fabrication, Black hole attack, Message tampering, etc. are extensively discussed [21]. The attacks on communication layers such as application, transport and physical layers are extensively discussed in [16, 30]. The few solution to such attacks are also proposed using cryptography, trust group framework, authenticated routing, secure distance vector and message transmission, ARIADNE, blockchain technology [14, 31]. Also, privacy concerns in vehicular communications are necessary to provide protection for the user data. In order to improve and provide reliable services, many researchers have identified various different techniques and approaches to maintain the user's privacy, some include the use of Group Signature, pseudonyms, identity based, mixed zone based, traceability, Misbehaviour detection, Revocation, etc. [21]. Security and privacy requirements in VANET should be taken into consideration when designing a robust system else malicious attack may ruin the service application of VANET. In this context, before putting VANET into practice, it is important to have an efficient secure mechanism which provides the required security and privacy services that overrides attacks in VANET. Several VANET based application require secure attack free traffic information for operation. The security level of such information can be improved by introducing a concurrent or alternate source of information that have reduced chance of attacks. The most common existing traffic information source is from traffic videos from surveillance cameras that can be used either as an alternate or backup source of traffic information when VANET based source is not available. As the attacks to images of traffic videos are not common and there are techniques to encrypt images to ensure secure communication of images to the processing centres [36], [37]. There are limited number of research works that have incorporated this concept. In [12] the author proposes image querying language for object recognition using image processing for vehicles equipped with camera for emergency application of VANET. Similarly, in [35]VANET based accident detection using image processing technique to improve security is presented. Both the works are specific to a particular application and are not robust in nature. In [20], a theoretical prototype of using a detection sensor for co-operative vehicle based congestion estimation application is discussed. Therefore, this paper proposes the idea of integrating other infrastructure to ensure the availability of information during the above mentioned challenging situations.

The technological advancements in hardware and software technologies congruent to sensors and advanced computer vision algorithms aid in providing abundant information from the captured images. The information extracted can be utilized to solve numerous crucial transportation related problems in traffic flow analysis, incident management, safety precautions, road usage control, etc. The attractiveness towards computer vision technologies is due to its cost effectiveness as well as the wide range of application supported by this technology [32, 9]. Thus, the other infrastructure used to ensure the availability of traffic information is video based system. It is also necessary to improve the precision of the information obtained using computer vision techniques in traffic video. The numerous optimized and high performing vehicle detection algorithms in the literature that uses a combination of vehicle features and image processing algorithm [38, 33, 13]. The traditionaly existing motion based detection method is Background Subtraction (BS) [7, 28]. Few of the popular approaches in BS include Running Average Method, Gaussian Models, Mixture of Gaussian Models, Codebook Method, Kernel Density Method etc [33, 4, 13, 5]. There are other state-of the-art technologies that are popular specific to object detection: You Only Look Once (YOLO), Region Convolution Neural Network (RCNN), VIBE, Deformable Parts Model (DPM), Single Shot Detector (SSD), Faster–RCNN, Evolving Box (EB), Aggregated Channel feature (ACF), etc. [38, 23, 18]. To summarize about the existing works, the current vehicle detection systems have different methods and approaches and their combinations are specific to properties such as camera angle, data capture reliability, applications etc. [39, 7]. The driving disparity of the environment is the main reason for a variety of computer vision algorithms and methods. Obtaining traffic information is the integral part of an ITS application hence the vehicle detection process might choke the entire application functionality. Therefore, there is a need to improve the accuracy of the conventional detection process at the same time reducing or least maintaining their existing processing time. To handle such requirements a simple, comprehensible improvisational scheme known as Spatial Traffic Video Content Processing (STVCP) architecture is proposed. It embraces and utilizes the color information's spatial properties in order to achieve improved results of vehicle detection with reduced computational cost. It is also developed in an effective way such that it is easy to be incorporated by any of the above vehicle detection algorithms. The details of the proposed framework for open exchange of traffic information from improved video content processing are discussed in the subsequent sections.

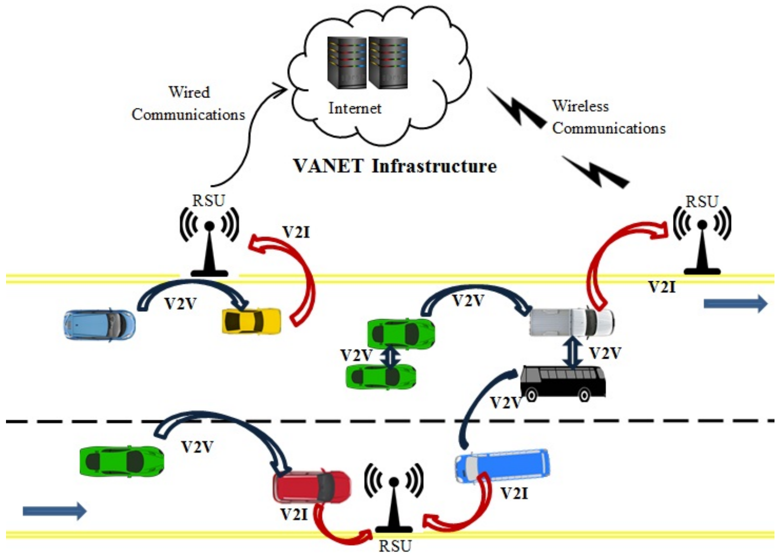


Figure 1: Co-operative Vehicles of VANET Infrastructure

3 Introduction to VANET and its Challenges

Before presenting the proposed framework, a brief introduction to Vehicular Ad-Hoc Network (VANET), its applications and challenges are discussed. VANET is the most recently developed technology to improve driving experience in terms of safety, comfort and efficiency. VANET infrastructure comprises of co-operative vehicles that act as mobile nodes equipped with OBUs and several Road Side Units (RSUs). It facilitates information exchanged through Dedicated Short Range Communication (DSRC) network among vehicles [3]. The information are described as Co-operative Awareness Message (CAM) with IEEE 802.11p or WAVE standards that contains parameters like vehicle id, Speed, timestamp, Latitude, Longitude, Lane, Others (E.g. traffic type and traffic information) that are essential for optimal functioning of ITS applications [6]. The basic two type of communication of CAM in VANET: The exchanges of information occurring through wireless communication among vehicles are called Vehicle-to- Vehicle (V2V) communication and similarly communications with vehicle and RSUs are Vehicle-to- Infrastructure (V2I) Communications. The CAMs obtained from the RSU are transmitted to Traffic Management Centre (TMC) which maintains it in databases. The raw data obtained are processed in the servers based upon their respective service applications and periodically updated at regular intervals to the database. A simple VANET infrastructure is symbolized in Figure 1. Numerous applications could make use of CAM obtained from this infrastructure and are broadly categorised into two types as in [21]. One includes applications that increase the safety aspects of travellers (safety applications) and the other includes applications that provide value added services like entertainment (user applications). In [19] the applications are classified into four categories and the respective applications are shown in Table 1.

Since the communicating nodes in this infrastructure are vehicles, it is highly challenging to have a continuous and assured connection as the network topology becomes extremely dynamic. Ensuring the quality and continuity of information flow becomes one of the major challenges in VANET [21, 6, 34, 29]. The other challenges in VANET are listed below:

- **Scalability:** When traffic density increases in a location (area/road segment) the number of vehicles communicating to a RSU increases. The RSU gets jammed or runs out of bandwidth for further communications. On such occasions, it is necessary to have a fault tolerant solution to back up the loss of information units.

Table 1: ITS Applications using VANET

S. No.	Application	Examples
1.	Active Safety	Alerts about dangerous road features, Pre-collision Warning, Incident warning – Breakdown Warning, SOS service, Blind spot collision, Brake system warning, Vehicle or infrastructure based road condition warning, Traffic lights violated warning
2.	Public Service	Emergency alerts- Emergency vehicle movement warning, Authorities support systems- Licence plate recognition, Vehicle safety inspection, stolen vehicle tracking
3.	Improved Driving	Alerts on crash, Map updates on maintenance, route alteration, route guidance, parking spot management, congestion information, Highway merge assistance, in vehicle signage
4.	Business/Entertainment	Vehicle maintenance related applications- Time to repair notifications, software updates, safety recalls, Mobile services- Instant messaging, Point of interest notifications, Enterprise Management applications- Fleet management, Rental car processing, Cargo Tracking, E-Applications- toll, parking, gas payments

- **Availability:** External or environmental factors such as time of the day, adverse climatic conditions, temperature, tampering or connection issues affects the enumeration of information for the application leading to disruptive availability of information.

- **Security and Privacy:** Security issues and attacks on VANET listed in Section 2 are the major challenge is exchanging information through a wireless network.

- **Context Awareness:** The enumeration algorithms are not compatible to changes in vehicle density or movement, traffic flow, and road topology. On the other hand, protocol designers should also consider the possible consequences the protocol may have on the physical world.

- **Quality of Service (QoS:** The QoS aware solutions are being developed to meet the emerging requirements of these applications. QoS has to be guaranteed by the network to provide certain performance for any given applications in terms of parameters such as delay, jitter, bandwidth, packet loss probability, and so on.

4 Proposed Traffic Information from Collaborative Framework (TICF)

VANET based approach for managing traffic using information from co-operative vehicles involves considerable propagation delays and low reliability based on the challenges discussed above. To resolve the aforementioned challenges, this paper proposes a Traffic Information from Collaborative Framework (TICF) for traffic management applications based on VANET. The proposed architecture of TICF is shown in Figure 2. The proposed framework adds the advantage of video based detection system with a VANET based system. It allows the integration of various types of sensors and technologies into a single framework. It provides the flexibility to support VANET during low-bandwidth and high-latency vehicular network environment and provides high reliability and accurate traffic status or information from video based system. The roles and responsibilities of the modules of the proposed framework are discussed below.

TICF describes an efficient way to acquire traffic information for a road segment for an application in VANET from traffic video system equipped in the same road segment. The proposed prototype framework comprises of three modules: Co-operative vehicle based system, traffic video based system and control centre system. The OBUs equipped in co-operative vehicles of VANET establishes a V2I communication to the nearby RSU or to the control centre to share information. The traffic video based system is used to collect data or images and communicate via RSU to the control centre. This communication across infrastructure is denoted as I2I communications. The RSU is an embedded system equipped with communication interfaces. It interfaces communication directly with the traffic video based system, wireless communications among co-operative vehicles and control centre using a web API. In the control centre, the information are collected, analysed, processed and stored in database with an object oriented model. The information obtained from traffic video system is processed using a proposed Spatial Traffic Video Content Processing (STVCP) architecture in the control centre to have highly accurate traffic information of the road segment.

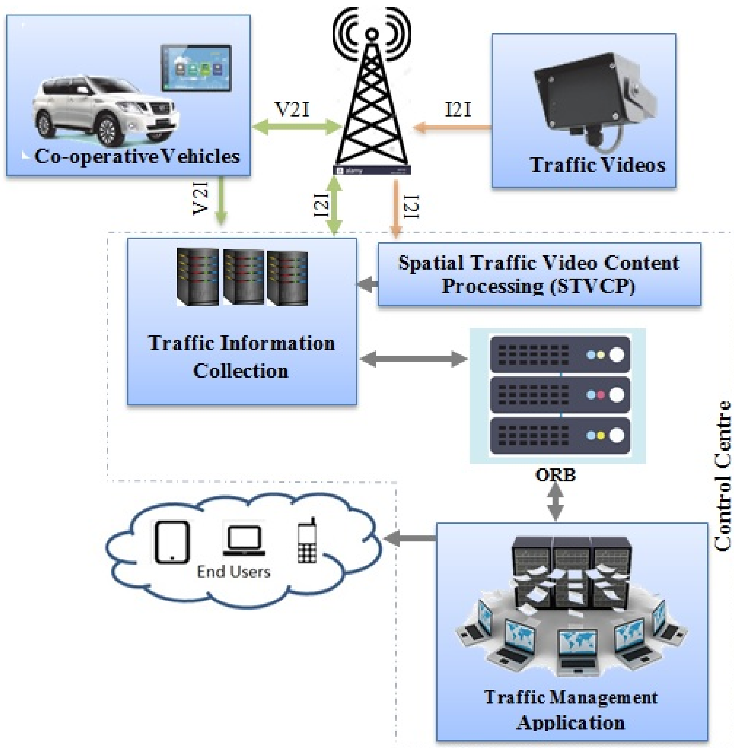


Figure 2: Proposed Traffic Information Collaborative Framework for VANET

The major component of the proposed framework that enable the flexibility and support of multiple sensor sources of information is from the Common Object Request Broker Architecture (CORBA). CORBA is a data standard or data interface design specification developed by Object Management Group (OMG). It enables collaboration among diverse programming languages, hardware and operating systems. It uses object oriented model to establish this standardisation. Object Request Broker (ORB) is the major programming component developed using Interface Definition Language (IDL). ORB acts as a middleware that takes care of the details in the client requests of objects and routing to its destination. [17, 40]. Subsequently, as the proposed framework is built upon CORBA the traffic information from co-operative vehicles and traffic videos are made generic and available for open exchange. In the proposed TICF, whenever a VANET based application request for traffic information, the ORB identifies the appropriate traffic information in the storage or database obtained from traffic videos to resolve the request.

4.1 Proposed Ontology of TICF

The detailed representation, relationships with concepts, data and entities of the proposed TICF are encompassed using ontology of the proposed framework. The schematic representation for ontology of TICF is shown in Figure 3. The set VANET applications $\in \{Applicationid\_1, Applicationid\_2, ...Applicationid\_N\}$ initiates request for traffic information. The information requested can be from any of the set origindestination $\in \{O-Did\_1, O-Did\_2, ...O-Did\_M\}$. Each origin- destination is sub divided into S road segments denotes as $\{Segment\_id\_1, Segment\_id\_2, ...Segment\_id\_S\}$. Each segment have traffic information such as velocity, speed, volume, area occupancy, etc., that are obtained from two sources $\{Sourceid\_1, Sourceid\_2\}$ representing co-operative vehicles and traffic videos respectively. Consequently, the ORB identifies the sources of traffic information requested by the application. The ORB defines the interface for traffic information by defining the source and method for enumerating the traffic information. The proposed framework stores the data from several sensors using object oriented model in order access from ORB. The flow of information described above for an application denoted as ONTO id_1. Similarly, other applications also have information flow structure given as {ONTO id_2,... ONTO id_J}.

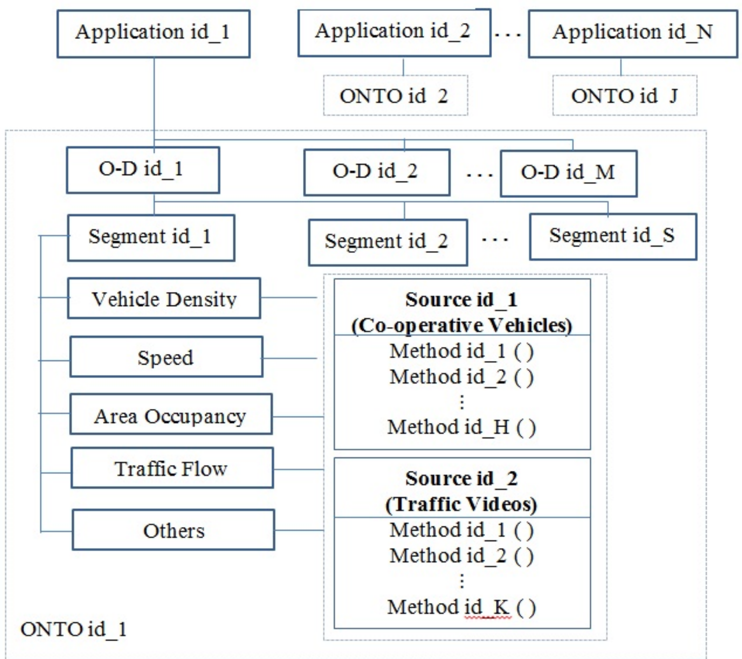


Figure 3: Ontology of TICF

4.2 Proposed Spatial Traffic Video Content Processing (STVCP) Architecture

Several real time traffic information such as speed, density, volume, etc are enumerated using computer vision techniques in the traffic video [22, 39, 32]. To improve the precision of VANET based application the proposed TICF uses computer vision infrastructure to obtain lost traffic information. To ensure the lost information obtained from traffic videos are precise with improved quality, this paper proposes a Spatial Traffic Video Content Processing (STVCP) architecture. The prime task of enumeration is the vehicle detection from traffic video which has to be accurate with reduced processing time. In order to address both this need, two modules are proposed in STVCP, namely Non-Recurrent Spatial Content Processing (RSCP) and Parallel Spatial Content Processing (PSCP), to improve precision of vehicle detection.

4.2.1 Non-Recurrent Spatial Content Identification (NRSCI)

In this module, the images in the traffic video that poses recurrent spatial information are eliminated to be processed for vehicle detection. The images or frames from traffic video are stored in an image buffer of size B. Non-Recurrent Spatial Content Identification (NRSCI) identifies the appropriate frames to be stored in the buffer for every F frame using critical segment of frame. The critical segments of frame are chosen by the user to define the crucial points where the movement of vehicles is predominant. The critical point selected encompasses pixels of radius R. The proposed NRSCI module is given in Algorithm 1.

Algorithm 1 Buff- S module

Input: Video Frame
Output:Buffer_1 [ ]
Begin
for n=1 to F **do**
  for i=1 to p **do**

$$CPValue_i = \begin{cases} 1 & \text{if } |(F_i^n - F_i^{n-1})| \geq Th_{buff} \\ 0 & \text{otherwise} \end{cases}$$

    CPSum = CPSum +$CPValue_i$
  end for
  if $CPsum \geq 1$ **then**
    Buffer_1[ ] = addToBuffer(CF);
  end if
end for
Return Buffer_1[ ]
End

where
n = 1 to F Frames
i = 1 to P critical points
CPSum = Total critical points having movement
addToBuffer(Frame) = Function to add current frame to buffer

The movement of vehicles in the frame are detected by computing the difference in pixel values between two consecutive frame (CPValue) and comparing it with the threshold value $(Th_b uff)$. Even when at least one of the critical segments has value above the threshold, the corresponding CSRF is stored in buffer and referred as Critical Frame (CF). The critical segment matching is a simple matching technique [8] which has a complexity of O(n2m) where n is the number of critical pixels selected and m is the number of frames for comparison. Buffer 1 and 2 are temporary storage space implemented with queue data structure, with two basic operations namely frame insertion and deletion. The selected CF are used for the vehicle detection process and the rest are eliminated from processing. This module helps in reducing the processing time of detecting vehicle.

4.2.2 Parallel Spatial Content Processing (PSCP)

Among several vehicle detection algorithms in literature, the motion based vehicle detection of Background Subtraction (BS) [7, 39] is used to describe the process of PSCP. BS is the most common and successful method for detecting movements of objects by taking a frame as background and comparing subsequent frames against the background. The reference frame used for subtraction and subsequent frame are defined as Background Image/Frame and Foreground Image/Frame (BI/BF and FI/FF) respectively. BI comprising of static scenes is compared against FI comprising of any type of moving objects. Hence the key step in any BS is to model the BI effectively [28]. During detection process, the existing detection process converts the frame of the video into binary or grey level image leading to loss of spatial information. This loss of information in a frame of video is avoided by considering all the three spatial color components of the image in Hue Saturation and Value (HSV) formats. But when processing the color component sequentially, it increases the processing time and computation by almost three times when compared to grey level or binary image processing. To reduce the time, a parallel system is put forth in this work as shown in Figure 4. All the process in this section are performed in parallel [25, 11, 24] for the three color components to preserve the valuable information of the video which eventually provides an enhanced quality of the result, thereby reducing the processing time. The process of parallel enumeration for BS methods including running average is presented.

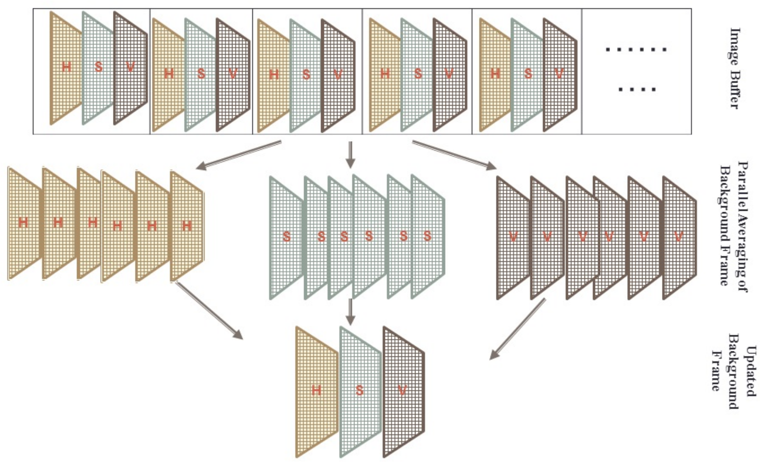


Figure 4: Parallel Spatial Content Processing (PSCP)

When the Buffer 1 of size B described in the previous section is exhausted with CFs, all frames in the buffer are averaged to obtain the Updated Background Frame (UBF). The sudden illumination changes such as birds flying, weather variations or any other change are taken care by this weighted averaging method as the UBF will be updated in quick intervals. The most advantageous process in NRSCI is that R-MPVIP establishes multilevel parallelism in BS using HSV color components. Each CF has three color components (HSV) and individual color component are weighted averaged to form UBF (UBFH, UBFS, UBFV) as coined from [25] are expressed Equation 1 and 2. The averaging of three UBF's are executed in parallel as shown in BS section of Figure 4.

$$ABF_C = 1/B \sum_{B}^{j=1} [a_M, b_N]_j \tag{1}$$

$$UBF_{C,i} = \alpha(UBF_{C,i-1}) + (1-\alpha)(ABF_c) \tag{2}$$

$$RI_{C,i}(a,b) = \begin{cases} 1 & \text{i}f|FF_c(a_M,b_N) - UBF_c(a_M,b_N)| > Th_{bs} \\ 0 & Otherwise \end{cases} \tag{3}$$

where C = H, S or V color component of frame,
ABF_C is the Averaged Background Frame of C^{th} color component,

$UBF_{C,i}$ is the Updated Background Frame of the C^{th} color component of i^{th} iteration,
B is the size of the buffer,
(a, b) is the pixel location of the frame of size M×N,
α is the weightage parameter,
$RI_{C,i}$ is the Resultant Image of C^{th} color component,
Th_{bs} is the threshold for background subtraction.
Equations 1 and 2 update the BI for every B frame in buffer. Once UBF is enumerated, Buffer 1 content is moved to Buffer 2, from where background subtraction is carried out. Buffer 1 is cleared off which helps in effective use of storage space for next BI modelling. Each CF is picked from Buffer 2 as FF (FF_H, FF_S, FF_V) and is subtracted with UBF (UBF_H, UBF_S, UBF_V). The Resultant Image of the C^{th} color component at location (a,b) is an image with intensity value either 0 or 1 (black or white). White represents the moving object detected from FF using threshold Th_{bs}. From RI, the detected vehicle properties are used to enumerate traffic information.

Thus, the above proposed framework for VANET presents an efficient way to ensure the availability of traffic information during adverse conditions such as network failure, low bandwidth, propagation delays, etc. TICF assures the availability from traffic videos that uses STVCP architecture to enumerate traffic information. From the proposed framework, precise traffic information are made available for VANET based traffic management applications without any compromise in loss of information. To evaluate the enhanced precision of the proposed framework a fuzzy logic based traffic congestion application of VANET is used.

5 Simulation and Performance Analysis

Initially, the accuracy and processing time obtained by Spatial Traffic Video Content Processing (STVCP) architecture of the proposed Traffic Information from Collabrative Framework (TICF) is analysed. The accuracy of vehicle detection is analysed using several benchmark traffic videos such as DETRAC, Koper and self recorded videos [38]. The videos were of different resolution such as 640 ×480, 720×480, 960×480, 1280×1024 etc. Some of the video formats include .asf, .mpg, .mp4 etc., The frame rate was set to 32fps with different traffic density. The algorithms were implemented in Visual Studio C++ with OpenCV and OpenMP library files. Algorithms that are native to OpenCV and available as open source are used for analysis [1]. They include running average, Mixture of Gaussian (MOG), Improved Adaptive Gaussian Mixture Model (IAGMM), fuzzy integral as in [33, 41, 4] respectively. For easier analysis on the performance, algorithms are tested with varied traffic conditions such as low medium and high with number of vehicles moving as <25, 60-100 and >100 respectively. Few observations of vehicle detection using STVCP in videos with low, moderate and high traffic are shown in Figure 5, Figure6 and Figure 7 respectively. The results show that the detection becomes easy and highly accurate for videos irrespective of the homogeneity or heterogeneity nature of the video. It shows that other algorithms that perform well for low traffic videos do not have similar performance for a high traffic. Whereas, results of using proposed work detection scheme seems to have consistent detection ratio. The overall accuracy of detection of vehicles irrespective of the traffic is 84.3%. This improved precision in vehicle detection is due to the PSCP module that uses the color component of the video effectively.

The other most important advantage of the proposed system is the processing time of traffic video from NRSCI. The average unit processing times excluding frame grabbing time for various methods is shown in Figure 8. It is seen that the processing time for low traffic and medium traffic are significantly low for the proposed STVCP as a result of NRSCI that filters irrelevant frames. As per the performance analysis, the STVCP saves up to an average of 8.5 hours of processing in a day which is 44% reduction in processing cost for low traffic background. The average processing time reduction is upto 23.2%. Thus

STVCP helps in identifying the vehicles better using PSCP and also drastically reduces the computational cost in a real time scenario using NRSCI.

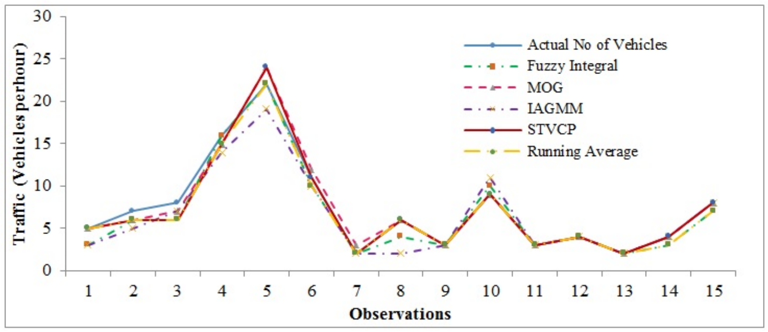


Figure 5: Performance of STVCP in Low Traffic

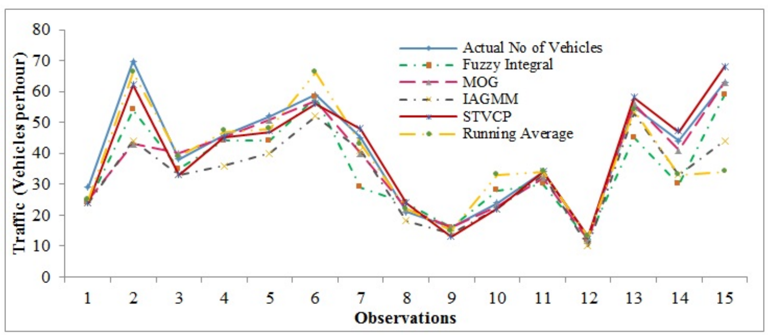


Figure 6: Performance of STVCP in Medium Traffic

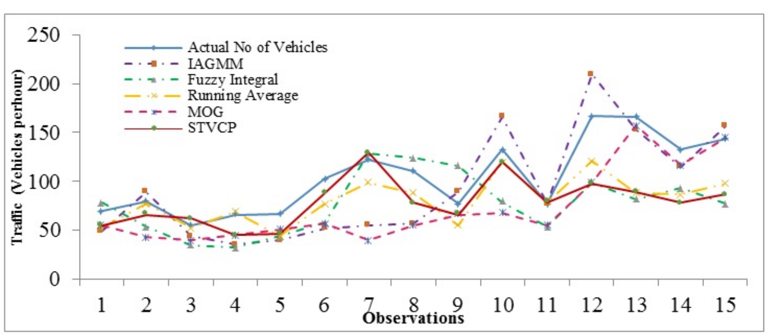


Figure 7: Performance of STVCP in High Traffic

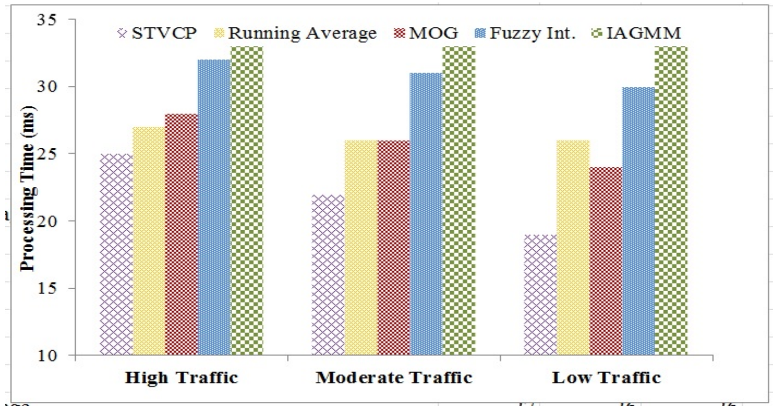


Figure 8: Processing Time using Proposed STCVP

The proposed Traffic Information from Collaborative Framework (TICF) is analysed using Traffic Congestion Rate (TCR) estimation application of VANET. Being a non-deterministic problem of TCR estimation, a fuzzy logic based controller is used as in [27, 20, 26]. The traffic information used for TCR estimation in this work are average vehicle volume and speed. The overall working of TCR estimation using fuzzy logic with volume and speed parameters are described in the following steps

1. The membership functions TCR estimation are defined in fuzzy logic controllers.
2. The input parameters (volume and speed) from co-operative vehicles of VANET are calculated, if data not available or require validation the requirement is initiated to ORB in TICF.
3. Reliable alternate source of available data from traffic video content using STVCP from CORBA are responded.
4. Input parameters are subject to the "if-then" rules and processed.
5. The outcomes of all the individual rules are combined and weighted into one single fuzzy set of outputs as TCR estimates.

For analysis the traffic information values of vehicle volume and speed from OBU and STVCP are accessed and maintained using CORBA simulator. The screenshot of ultra CORBA simulator is shown in Figure 9. Next, the performance of TCR application in VANET with TICF is analysed using MATLAB. The values for input parameters for fuzzy logic controllers from co-operative vehicles are simulated in Network Simulator (NS2) to mimic the movement of the vehicles from the traffic video of commercial area. The input parameters from traffic videos using STVCP are available for TCR estimation. The simulated value of speed and traffic volume is shown in Figure 10a and Figure 10b. Few observations of simulated loss of information for VANET application to show the effectiveness of including traffic video based system in TICF is shown in Figure 11. The availability and unavailability of traffic information is represented as 0 and 1 respectively.

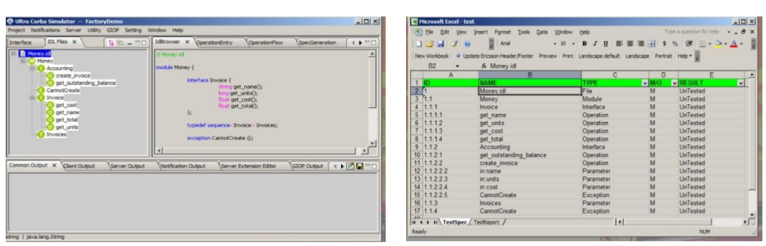
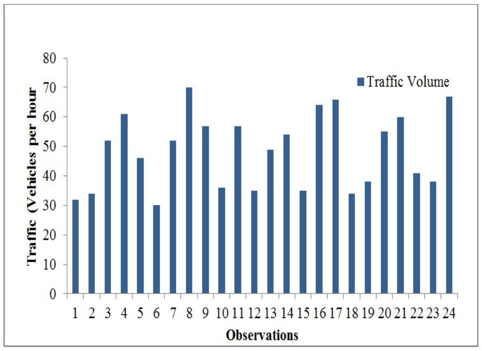
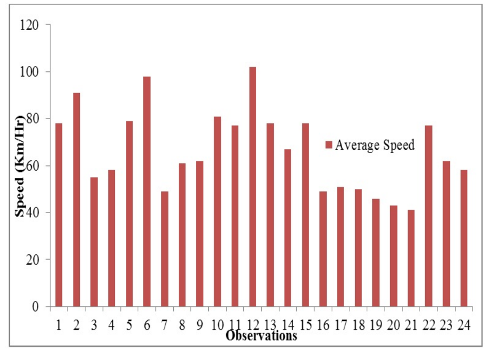


Figure 9: Screenshot of Ultra Corba Simulator



(a) Simulated Traffic Volume



(b) Simulated Average Speed

Figure 10: Simulated Value of Volume and Speed for VANET based TCR Estimation

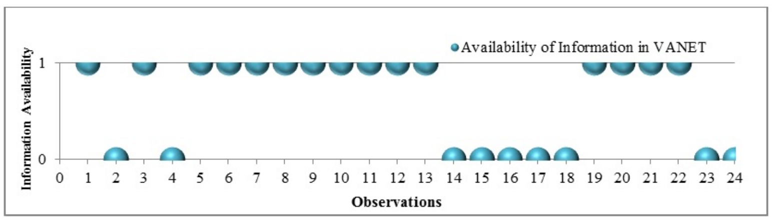


Figure 11: Simulated Loss of Information for VANET Application

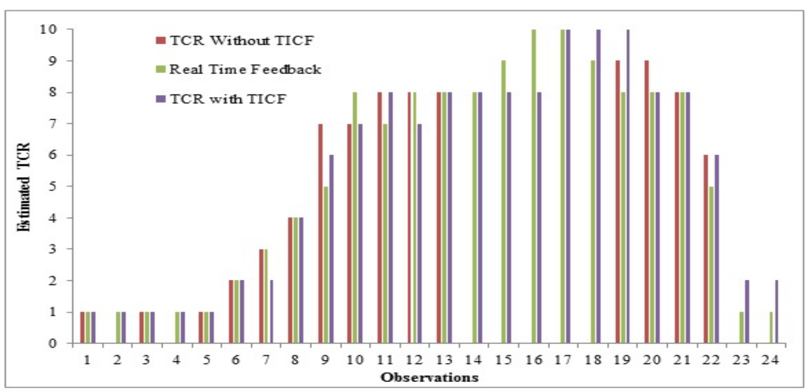


Figure 12: Traffic Congestion Estimation using TICF

The loss of information as in Figure 5 are compensated using traffic information from STVCP in TICF. The results of TCR estimation using simulated traffic information from co-operative vehicles of VANET with TICF and without TICF are shown in Figure 12. Being fuzzy parameters the TCR value ranges from 1 to 10, 1 being least congested and 10 being completely jammed situation. From Figure12 it is seen that the independent TraCo estimation denoted by TCR without TICF could not operate during increased vehicle density at peak hours (1400 to 1800 hrs) due to limited network bandwidth capacity for commercial area. But TCR with TICF was able to initiate data request (on demand request) for volume and speed parameter values to ORB which in turn responded with the traffic information from traffic video system of STVCP. This lead to successful operation to provide accurate TCR values during such unavailable hours. Thus from simulating TCR with periodic and on-demand data requests to ORB, it is seen that TICF validates and improves the efficiency and consistency of the congestion estimation service.

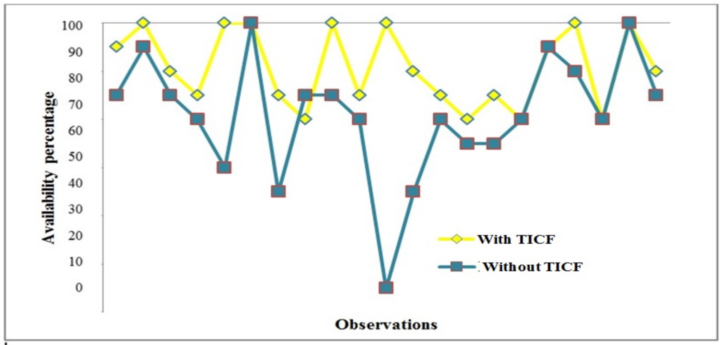


Figure 13: Traffic Information Availability Percentage using TCIF for TCR Estimation

The efficency of TCR estimation with proposed TICF and without TICF are compared with the percentage of availability of traffic information. The total availability percentage for several simulation of traffic information for VANET based TCR estimation is shown in Figure 13. It is seen that TCR estimation with TICF ensures the requested or unavailable traffic information are assured availability with 90.2% from alternate source of traffic video using CORBA leading to improve performance of TCR application. From overall performance analysis it was encountered that the accuracy of TCR estimation with TICF is 93.4% compared to the real-time congestion feedback values.

6 Conclusion

Vehicular Adhoc Network (VANET) based infrastructure supports a broad area of research establishing several service applications for traffic management in Intelligent Transportation Systems (ITS) to regulate and provide maximum traffic related information to travellers. The integral part of any ITS service application is the traffic information such as speed, volume, density, etc., that ensures its seamless functionality. During adverse situations in VANET such as low bandwidth, propagation delays, sensor integration, overhead issues during rise in number of vehicles, packet loss, etc., there is a need of an alternate source to provide backup to the traffic information. Hence, the other current and commonly existing ITS technology to enumerate traffic information is from traffic video that uses computer vision infrastructure. This paper proposes a new infrastructure known as Traffic Information from Collaborative Framework for VANET based ITS applications to ensure the availability traffic information from traffic video content that uses a novel Spatial Traffic Video Content Processing(STVCP) architecture. TICF uses Common Object Request Broker Architecture (CORBA) to standardise the data for open exchange of traffic information. The performance of the proposed architecture and framework is analysed using a VANET based Traffic Congestion Rate (TCR) estimation application using traffic volume and speed information from simulated co-operative vehicles and real time traffic videos. From the results, it is seen that proposed STVCP improves the precision of the traffic information with 84.3% irrespective of traffic video properties and reduces the processing time by 23.2%. With the precise traffic information from STVCP, the overall availability assurance to VANET application is 90.2%. The results also show an improved accuracy of TCR estimate upto 93.4% while using the proposed TICF. Thus, the proposed TICF improves the precision of the VANET based traffic management applications by considering the traffic information of traffic video content during information loss.

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