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Virtual Detection Zone in smart phone, with CCTV, and Twitter as part of an Integrated ITS

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Abstract- In this proposed integrated Intelligent Transport System, GPS enabled smart phones, and video cameras are used as traffic sensors, while Twitter is used as verifier. They are attractive because they are non intrusive, and consequently more practical and cheaper to implement. Our novel Virtual Detection Zone (VDZ) method has been able to map match by using pre-determined check points. VDZ speed accuracy ranges from 93.4 to 99.9% in higher speeds and it only needs one longitude and latitude coordinate, to form a detection aware zone. Also by using ANFIS we show that a more accurate traffic condition can be obtained using our three sources of data.

Index terms: Closed-circuit Television (CCTV), integrated Intelligent Transport System (ITS), Traffic data, vehicle detection, Virtual Detection Zone (VDZ), Adaptive Neuro Fuzzy Inference System (ANFIS).

I. INTRODUCTION

Traditional traffic monitoring technologies consist of on the road sensors, which are necessary but not sufficient because of their limited coverage and expensive costs of implementation (including time needed to lay the sensors on target roads) and maintenance [1]. In general, traffic can be counted using two methods: the intrusive and non-intrusive methods (Figure 1 shows this).

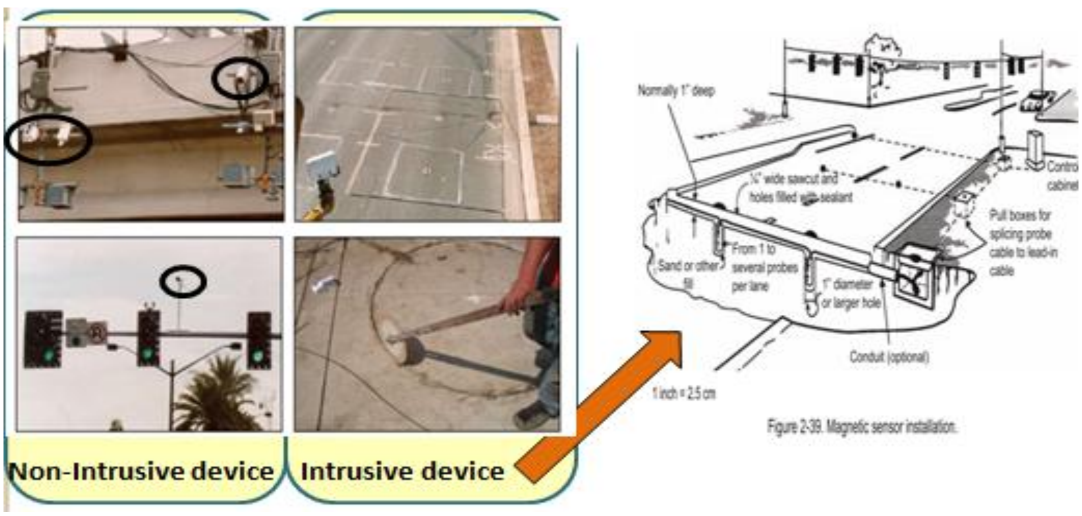


Figure 1. The non-intrusive (e.g. video camera and Radar/Ladar - encircled), and intrusive (e.g. inductive and capacitive/magnetic devices, need to be buried in the road), as traffic sensors, illustration is modified from [2]

The intrusive method basically consists of a data recorder and a sensor being placed on or buried in the road. This method includes (but not limited to): pneumatic road tubes, piezoelectric sensors, and magnetic loops (also called inductive loop sensor). Historically, traffic flow sensors were utilized since the discovery of sound sensor in the 1920s [2], [3]-page 36. More detailed information about the flow sensor evolution can be found in the same references. Because of the highly intrusive characteristic of inductive loop detectors, the relatively high cost of deployment and maintenance, the quest for researching a reliable and cost-effective alternative system, which can provide traffic data at the same accuracy level as inductive loop systems, while minimizing the disruption during installation and maintenance, has been underway for some time.

The non-intrusive technique is based on remote observations, which includes: manual counting, wired and wireless sensors, like: passive and active infra-red, passive magnetic, radio frequency or micro wave Radio or Laser Detection and Ranging (Radar or Ladar), and video image detection. The motivation of developing wireless sensor networks based surveillance system is to provide a direct replacement for the inductive loop systems, or to complement the use of other existing traffic sensors and to extend the coverage of Intelligent Transport System (ITS) applications. Video camera is another non-intrusive sensor already shown in Figure 1. In general [4], vehicle recognition must cope with a number of limitations that complicate the task: vehicles are generally of similar shapes, similar in sizes, but can be seen differently due to: reflections, shadows, varying weather and quality of light, vibrations (e.g. for cameras installed on bridges), different angles of view. Further on, the requirement to distinguish sub-classes such as minivan vs. car vs. taxi complicates the task. Although in urban ITS, it is more common to use broader categories of road user such as car, van, bus and motorcycle. One group of researchers in [5], has adopted a manual approach to segmentation. They aim to discover the potential of using simple low level features to achieve high levels of classification performance by filtering out noise before the image segmentation step. Following this idea, in our future work we would like also restrict ourselves to a fixed existing un-calibrated camera [6][7][8][9] in an outdoor non-structured environment which captures information of a simple traffic scene under not so low visibility conditions. Other researchers have used calibrated cameras to obtain more accurate speed measurements and we have adopted this method as an initial step. This method is rather impractical as existing video cameras must be calibrated first. Maduro et al [10] [11] have used rectified video images to calculate the vehicle speeds. While Garibotto et al [12] have used license plate to track the vehicle and then calculate its speeds. In fact there are a number of other ways to calculate vehicle speeds such as in [13][14][15][16].

Twitter can be another non-intrusive source of traffic data. Related research was recently carried out by Endarnoto, et al. [17] and more recently by Singh et al [18], in London. We have attempted to extract traffic updates from the Twitter account of the Traffic Management Centre (TMC) of Jakarta Metropolitan Police (Polda Metro Jaya) (@TMCPoldaMetro) in [19] and in this paper, by providing our own Twitter data to simulate it. In previous study Natural Language Processing (NLP) technique based on Context-Free Grammar (CFG) parser, has been used. But in [20], it has been found that most tweets (95%) do not use grammatical language. Only a total of 54 sample tweets (5%), which mostly are from online portals such Kompas.com and Detik.com, have used grammatical language. This is why for traffic updates, the use of NLP techniques have been abandoned. This preliminary analysis is important to design the analysis component of our system, which has required an identification of the nature of the texts to be processed.

Mobile phones can be used as traffic sensor, when location data of the user can be determined via an application (agent), either by using US Global Positioning System (GPS) or from other navigation satellites such as: Russia's Glonass and Europe's Galileo [21] [22] [23] [24] or from non GPS enabled phones, using Cell ID [25] or Internet based devices [26]-[27]. It is noted also that as technology progressed, the corresponding speed difference has become smaller or is considered reasonably accurate, i.e. between the inductive loop data and probe vehicle, using Global Positioning System/GPS enabled phones data, now, is in the range of 1.2 - 3.3% [28]. It has been reported in [21] that speed data from GPS enabled devices is less accurate during congested periods and for arterials. This study also aims to prove that as traffic sensor, mobile phones can provide accurate vehicle data speed at lower speeds.

Preliminary work has been conducted in our papers [29], [30], [19], [31] and are presented again in this paper, with more work on the three already mentioned traffic sensors. In [32], it has been suggested that more CCTV as well as other sensors, should be utilized to localize the solution for congestion. The work in this research is in line with this thought. In this case we propose the use of GPS enabled mobile phones, existing CCTV and existing Twitter data as traffic condition verifier. In the final section we will also present a case in which we utilize the algorithm of Adaptive Neuro Fuzzy Inference System (ANFIS) in order to describe the traffic condition by using the 3 sources of traffic data. Another way to solve this kind of problem is by using data fusion [33], [34].

II. SENSORS IN INTEGRATED ITS

Various architectures have been reviewed in [35] [36], to be acquainted with future challenges in developing distributed multi-sensor surveillance system, especially in terms of communication or integration between different modules of communication protocols and the creation of metadata standards. In our previous work [37] we have attempted to provide intelligence to the traffic light system with swarm-self organizing map.

In our proposed integrated ITS architecture, there are 3 actors, or 2 traffic sensors and 1 traffic verifier. Hand phones with location data acquisition, require user's interface to act as agents, while Twitter as a second actor, requires dedicated users to feed in traffic data. Thirdly, CCTV or video cameras require no users, but their video images must be collated and processed to extract useful traffic data. The embedded application or agent will have to perform various tasks, such as, comparing current GPS coordinate to the nearest detection coordinates, and assigning road ID. As part of the system, a database server, shown in Figure 2, will collate the data (as well as, combine, and arbitrate) from multi agents of hand phone traffic sensor, filtered data from CCTV, and Twitter.

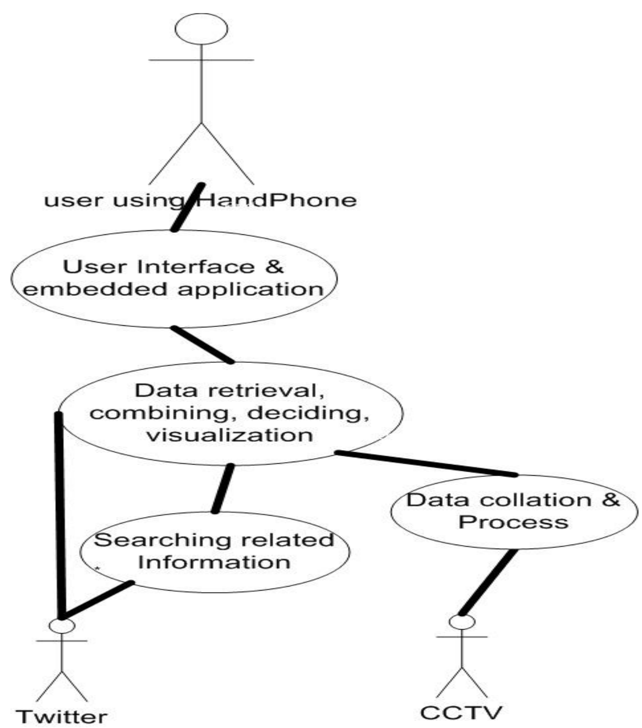


Figure 2. Use Case of the proposed Integrated ITS's architecture

Figure 2, shows the Use Case of our proposed integrated ITS architecture. In it we plan to have 3 actors, or 2 traffic sensors and 1 traffic verifier. Hand phones with location data acquisition, require user's interface to act as agents, while Twitter as a second actor, requires dedicated users to feed in traffic data and thirdly, CCTV or video cameras require no users, but their video images must be collated and processed to extract useful traffic data.

In summary, the Integrated ITS which is under construction at Universitas Indonesia's Faculty of Computer Science will look like Figure 3, in a form of block diagram. Firstly, an activated mobile agent/application in a hand phone will receive its location coordinates (i.e. longitude and latitude) from GPS or Cell-ID information, then it will detect whether the client is inside a certain zone as it moves along a road (called VDZ longitude and latitude coordinates or GPS coordinates, which came our server), and after three valid coordinates, it is given a Road Identification (Road_ID), and consequently, a number of information is extracted from them e.g. speed, direction, time stamp, and the latest GPS coordinates. The latest GPS coordinates are then used by the agent to obtain another portion of a digital map from querying Google map, or in the future, from our own server. A more detailed description of this process will be shown in Figure 4.

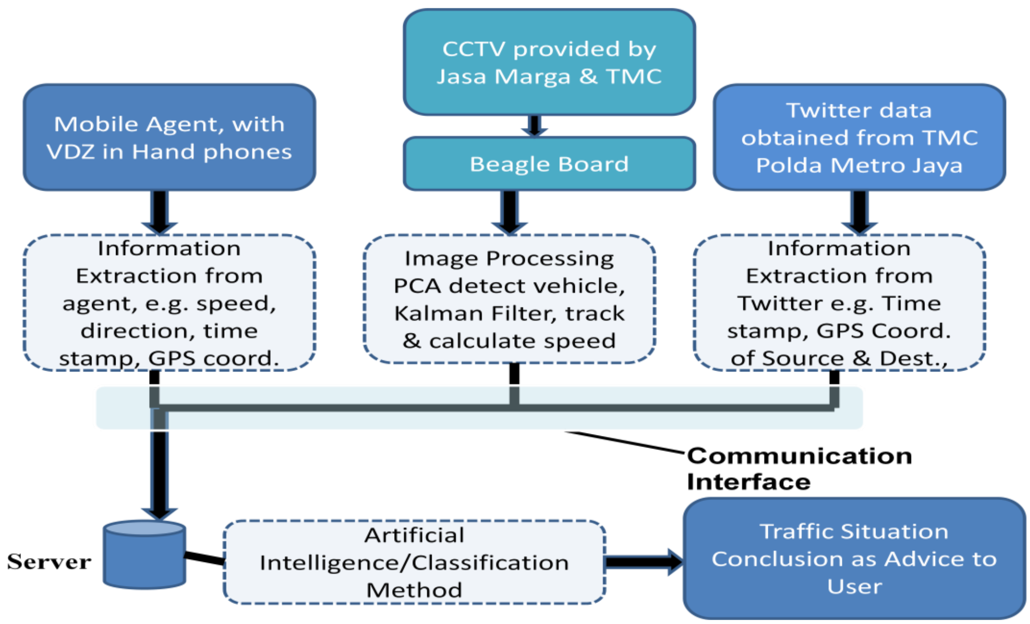


Figure 3. Integrated ITS under Construction at Universitas Indonesia's Computer Science Faculty.

The second block in Figure 3 is the CCTV, which consists of video cameras, provided by Jasa Marga and TMC – Jakarta's Police department. Each video feed from the CCTV will be processed by a Beagle Board (Data Collation and Process as Figure 3), which will include among other things: Image processing, vehicle classification, tracking and speed estimation. Initially, the Beagle board has been used to emulate the functions of high performance server, which would be available in the near future. While in the third block of Figure 3, traffic situation is extracted from TMC's Twitter data. Finally, the relevant data from three traffic sensors is sent via a communication interface to a server, and is processed to give a useful traffic advice to the user. In the following section, the inner workings of these 3 sensors are discussed in detail, in sub sections A to C.

A. *Smart phone as Traffic Sensor*

Many researchers have done ground breaking work in order to make mobile phones practicable, as traffic sensors. It has been found that the smart mobile phone (both GSM and CDMA based), from several references [38], [39], [24], [40], [21], [23], [41], is considered as a suitable device for location finder or traffic sensor. To provide location data, a hand phone must use either GPS (data obtained directly from satellites), A-GPS (data obtained from phone network), Cell-ID, or Wi-Fi devices, or a mix of them. Based on a our recent experiments, as well as in [30], it has been decided that the circle of VDZ should be about 50 to 100 meters in radius, and to make the average speed measurement valid, minimum penetration rate must be satisfied. This requirement is discussed next, and is followed by the use of parallel threads in VDZ system.

i) Penetration rate

The average speed calculation, using only a few agents for a certain section of a street, would be valid if the minimum penetration rate is satisfied. Concurrently, we are devising a way to ensure that minimum penetration rate is satisfied [42], which should be greater than 2-3%. This means the minimum number of agents should be more than 2% out of the total incoming vehicles during the period of the experiment. This rule also applies to our average speed calculation from video images of CCTV.

Similarly as in [23] [39] [40] [43] [44] [45] [46], we apply limitations on the experiment (in our case, one target road and 3 mobile agents), and the total number of cars is calculated when the agents/our cars have appeared in our video camera until they have reached a certain road length in order to estimate the car speed. We call this period of recording and speed measurement as a cycle, as the agents will come back again and again, to the same video view, around the chosen target or road circuit. The results, which include our penetration rate, are presented in Table 3.

ii) Parallel threads in VDZ system

The whole process inside a VDZ system can be described in this way. The application in the client's GPS enabled smart phone, acts like an agent, there are 3 parallel threads used i.e. VDZ timer, GPS, and VDZ sorting threads, as presented in Figure 4. Note that from GPS thread (located in the Read process of VDZ Timer thread), the server can tell where exactly the agent is, by looking up the VDZ_ID, a Road_ID can be assigned. VDZ_ID will be sent by the agent every 3 valid VDZ. These VDZ check points are compared to the current data position from GPS.

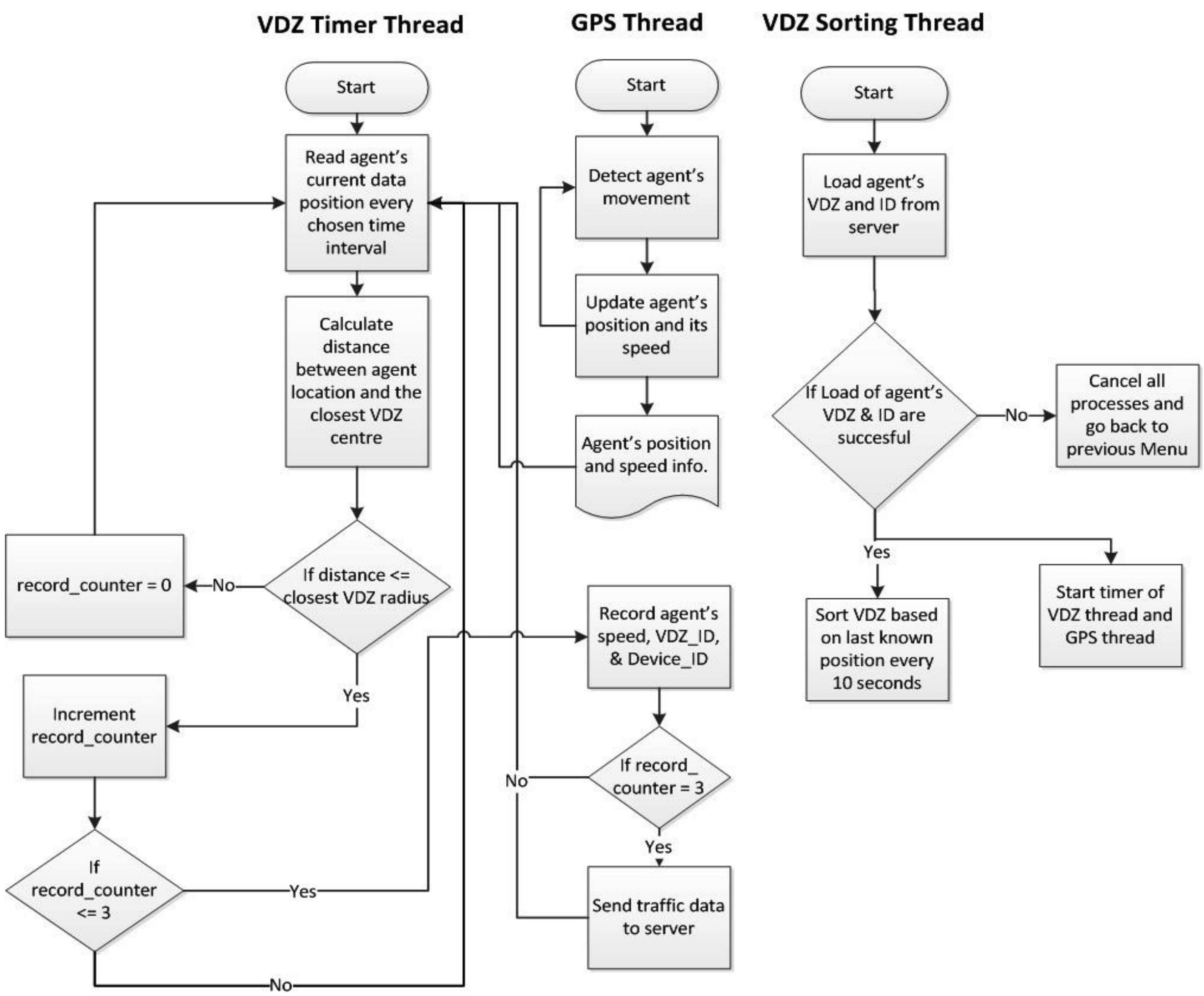


Figure 4. Flow chart of the 3 parallel threads used. a) VDZ timer b) GPS and c) VDZ sorting threads

The comparison process is performed in VDZ Timer Thread, for every second, which is shown again in Figure 4. We use a counter to emulate a timer. One second is deemed to be quick enough, from a simple calculation. VD circular zone of 100m in radius means, 200m of diameter. If a car travels 150km per hour, it will cover 41.7m in one second. This means VDZ Timer Thread, theoretically, can get up to 4 detections (200/41.7). If a car travels only 100 km/hour then in one second it will cover 27.8m, or up to 7 detections. While in the VDZ Sorting Thread, the sorting process is performed every 10 seconds (for our experiments we also try every 2 seconds).

B. CCTV as traffic sensor

The police and transport departments, as well as, a number of privately owned companies in Jakarta, have utilized CCTV as the source of information in surveillance and traffic management. However, in the case of CCTV, its images are only used to observe the traffic manually, without any automatic system which can detect the condition of each lane. In our previous research efforts of computer vision [47][48][31], traffic information has been extracted from the recorded video images. One of our main reasons to use CCTV as traffic sensor is because Jakarta is one among many cities in Indonesia, which has the largest number of CCTV [49] already installed. But even in Jakarta, no automatic system has been applied to detect the traffic conditions. Basically many methods have been proposed in [6], [7], [8], [9], [10], [12], [13], [14], [15] especially for vehicles speed estimation using video processing via CCTV.

Further more in our previous research [47], [49], [31], we have developed a system which can detect a vehicle, track it, and count the number of vehicles in a certain period and measure its speed. Haar-like features are used to detect the vehicle, as the main feature of vehicle detection. Weak detection (AdaBoost) is used to perform classification between the target vehicle and non target vehicle. While Kalman filter is used to track the vehicle, so that the target vehicle will not be accounted for repeatedly in different video frames. An adaptive method is adopted in [47], [49], and it is implemented in to a Beagle-board™. This board has been used to emulate a High Performance server which will take all the mentioned video image processes. The High Performance server, shown already in Figure 3, will also process all the data for the other two sources, namely Twitter, and smart phones. Adaptive here means to be able to give appropriate waiting time for the traffic lights in the intersection, according to the car density in that intersection. In particular, Distributed Constraint Satisfaction Problem (DCSP) method has been applied to give the needed waiting time for the traffic lights, to suit the car volume distribution for each lane. The consequent research [31] is to calculate the car speed on a particular lane as one of the determining parameters of the traffic condition. Machine learning (Haar training) method has been used to train the system. This system has three major steps, namely, i) Vehicles detection, ii) Vehicle tracking, and iii) Vehicle counting [47]. These steps are described in the following paragraphs.

i) Vehicles Detection

Figure 5 shows the Speed estimation architecture using CCTV employed in our ITS [31].

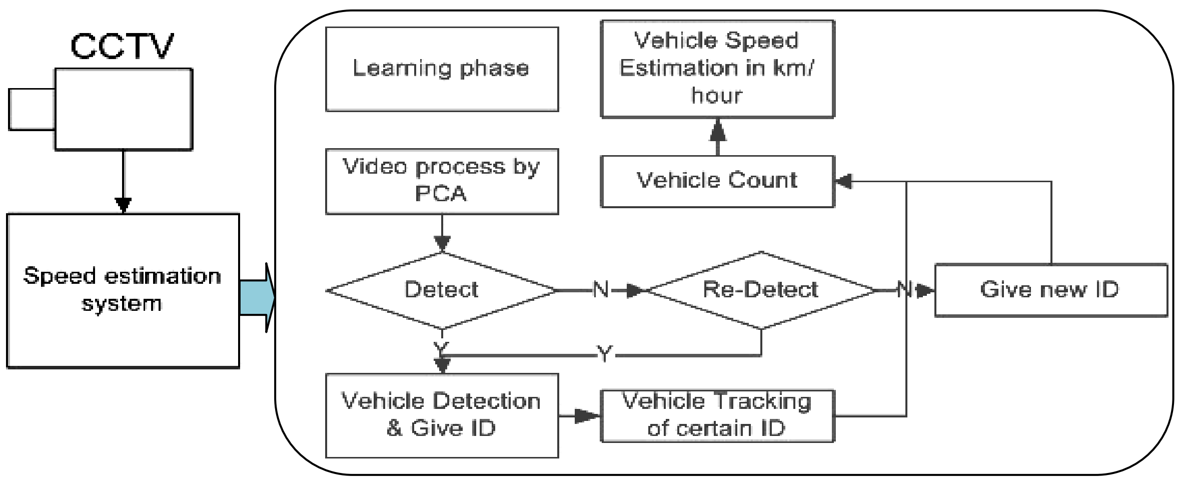


Figure 5. Speed estimation architecture using CCTV employed in our ITS [31]

As mentioned before, the vehicle detection system has been developed in our previous research [47][48][31]. Haar training or Machine learning is a method which uses supervised classifier.

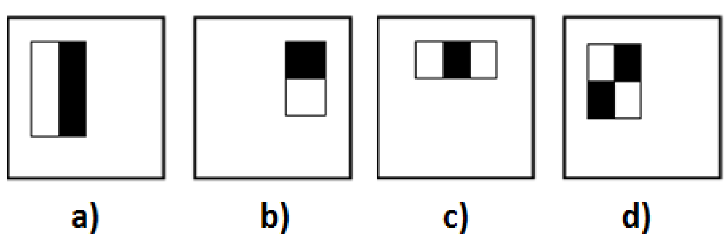


Figure 6. Harr-like features used for vehicle detection. a-b) 2 rectangle c) 3 rectangle and d) 4 rectangle filters

While AdaBoost, which is commonly, called weak classifier, is adopted to classify the object to be detected in the data training stage. In this training method, positive image (Object) and negative object (non-Object) are required. For the training, 5000 positive images from our experiment are used in approximately one week. The feature shape of Harr-like features, (Figure 6) has been developed in [50]. The result of a completed training process is a model which can be used by Haar cascade classifier, to detect the vehicle of interest.

ii) Vehicles Tracking

Rudolph E. Kalman is the inventor of Kalman filter, published in 1960. It provides a recursive solution to a discrete-data with linear filtering problem [51]. Kalman filter is basically a mathematical formula that applies the type of predictor-corrector estimator. This method can reduce the estimated error covariance. Figure 7 shows two processes, running recursively, namely "prediction" and "correction", both collaborated in Kalman filter method while the object being tracked is running. Euclidean distance is used to provide position and size prediction [52], [48]. Equation (1) shows the Euclidean equation for position change. Equation (2) is an equation to measure the size change. Both Equations are used to predict the object position in current position. The earlier position is required by a process to predict that position.

$$d_{coordinate}(x, y) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

$$d_{size}(w, h) = \sqrt{(w_2 - w_1)^2 + (h_2 - h_1)^2} \tag{2}$$

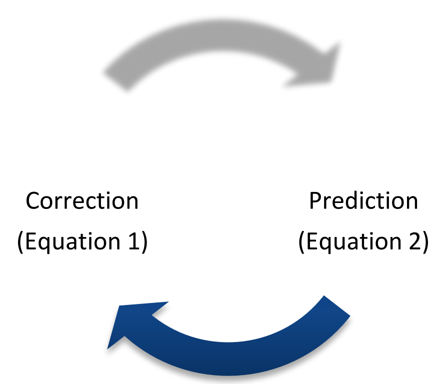


Figure 7. Turn-around process, called "Correction" and "Prediction" in Kalman filter method

iii) Vehicles Counting

A rather simple method is utilized in car counting. A small procedure is called when a certain car ID is found, then it will add to the number of cars for that particular car ID until the characteristics do not match. A new car ID is generated when none of the characteristics already stored match that car. After which tracking with Euclidean distance is performed, and when the resulting distance and size are not much different, it is assumed that object is same car. The algorithm can be described in the following:

```
INITIALIZE
REPEAT
    // Read Image File
    REPEAT
        // Read image frame
        // Do check car characteristics
        IF (car matches certain Car ID) THEN
        //      CarID_counter = CarID_counter + 1
                ELSE
                // Create new ID;  New ID_counter = 1
        END IF
    UNTIL image frame process ends
UNTIL image file ends
```

C. Twitter for traffic verification

Traffic data obtained from Twitter account, which publishes traffic information in real time, allows the Twitter server to get the actual traffic information.

As mentioned before, in this paper, we have attempted to use our own observers to simulate the Twitter from TMC of Jakarta Metropolitan Police, and like TMC Twitter, our observers have published the traffic data manually, and their data are then retrieved from the Twitter server.

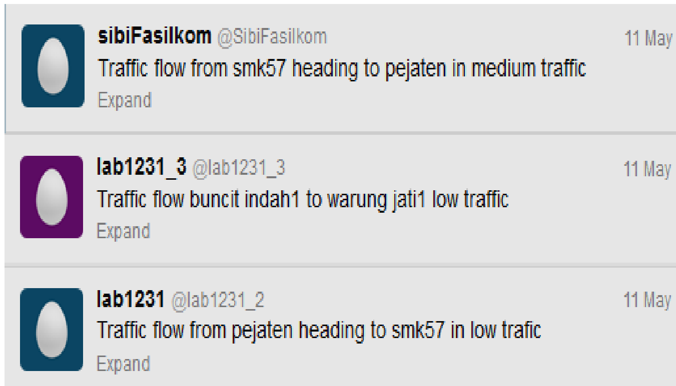


Figure 8. Tweets containing traffic information at each monitoring point which has VDZ and CCTV

The information obtained is a text containing statement that states the condition of the road at the time when the tweet has been published. The information about the traffic conditions from our target road will subsequently be used as training data label, for data classifier which is used for classifying traffic condition using information obtained from CCTV and VDZ. In [19] classification is done by using Learning Vector Quantization [53], whereas in this experiment, our data is classified by using Adaptive Neuro/Network Fuzzy Inference System [54] [55] and also using different attribute from [19].

The implementation of Adaptive Neuro Fuzzy Inference System for classifying traffic condition is described further in the next section. There are three twitter accounts used to verify traffic condition. The accounts are lab1231_2, lab1231_3, and sibifasilkom, as shown in Figure 8. When our cars pass by (carrying our agents in the smart phones) at different monitoring location, (each car has a VDZ in smart phones, as agent), our Twitter observers manually enter the traffic conditions in to those accounts. Each account tells the traffic condition for that specific location. Also our CCTVs placed on the bridges at the same time and same location have recorded the same event. To make the twitter data processing simpler and easier, as shown in Figure 8, every tweet-traffic-information has the same format. The format is: "traffic flow from <*source*> heading to <*destination*> in <*condition*>", where <*source*> and <*destination*> signify the section of the road which CCTV and VDZ have been placed. The <*condition*> has three possible values: "low traffic", which means that the road monitored has a low vehicle density; "medium traffic", which means that the road is dense enough to make the vehicles move slowly; "high traffic", which means that the road is really dense so that vehicles would eventually stop moving (traffic jam).

All tweets of traffic information published by the three accounts can be retrieved by requesting the Twitter API service. Each tweet is then processed to be tokenized for extracting necessary information based on our/TMC token categories. The categories are:

1. Time Stamp, containing information when the tweet is made. This information is required to enable data matching between VDZ and CCTV.
2. Source, is the location where vehicles come from on the way to a certain destination.
3. Destination, is the location where the vehicles want to go to. This is also the location of the observer, where he/she has observed and sends his/her tweet.
4. Condition, is the state of the traffic condition, based on the observer's considerations (which should be either low, medium or high traffic).

Further data processing (from CCTV, VDZ, and Twitter) is carried out by the server. Correlation of data from CCTV, VDZ, and twitter are obtained from time distance when the data have been created. After data grouping, the data is ready to become training data for multi-label classifier, which produces an output that describes traffic condition conclusion. This condition can either be: "low traffic", or "medium traffic", or "high traffic". This classification is needed because information obtained from twitter is manually generated by human observer, consequently that kind of information is not always available. That is why the conclusion of the traffic condition should be acquired from data classification with VDZ and CCTV as input parameters.

III. INTEGRATION OF ITS DATA USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Adaptive Network-based Fuzzy Inference System, in short ANFIS, was first introduced by Jang in 1993 [54]. ANFIS provides a basis of constructing a fuzzy if-then rules [56] with appropriate membership functions to generate the predicted input-output pairs. In this integrated ITS we have proposed the use of ANFIS to integrate the traffic data from our three sources.

Each function must have equal quantity of membership functions, and rules. ANFIS can be described by first-order rules of Sugeno fuzzy model.

Rule$_{(1)}$: **IF** x *is* A_1 **AND** y *is* B_1,**THEN** $f_1 = p_1x + q_1y + r_1$

Rule$_{(2)}$: **IF** x *is* A_2 **AND** y *is* B_2,**THEN** $f_2 = p_2x + q_2y + r_2$

Legend:

- x, y : Input vectors
- A_i, B_i : Fuzzy Set
- f_i : The output which is in the fuzzy area made by fuzzy rule.
- p_i, q_i, and r_i are the determining parameters which are created during the training process.

A and B are labels of fuzzy sets characterized by appropriate membership functions. Due to their short form, these if-then rules are often applied to capture the imprecise decisions of reasoning that have been accounted for, in the human ability to make decisions in an environment of uncertainty and imprecision. ANFIS algorithm model uses two rules which are described in Figure 9. In this diagram, the circle-symbol depicts fixed node and the box-symbol depicts adaptive node. ANFIS has five layers, and each layer works in the following ways:

Layer 1, all of which are adaptive nodes. The output of layer 1 is the fuzzy membership value of the input. The Output is described in equation (3), where *i* is the node number [57]:

$$O_{1,i} = \mu\ A_i\ (x),\ i = 1,2$$

$$O_{1,i} = \mu\ B_{i-2}\ (y),\ i = 3,4 \qquad (3)$$

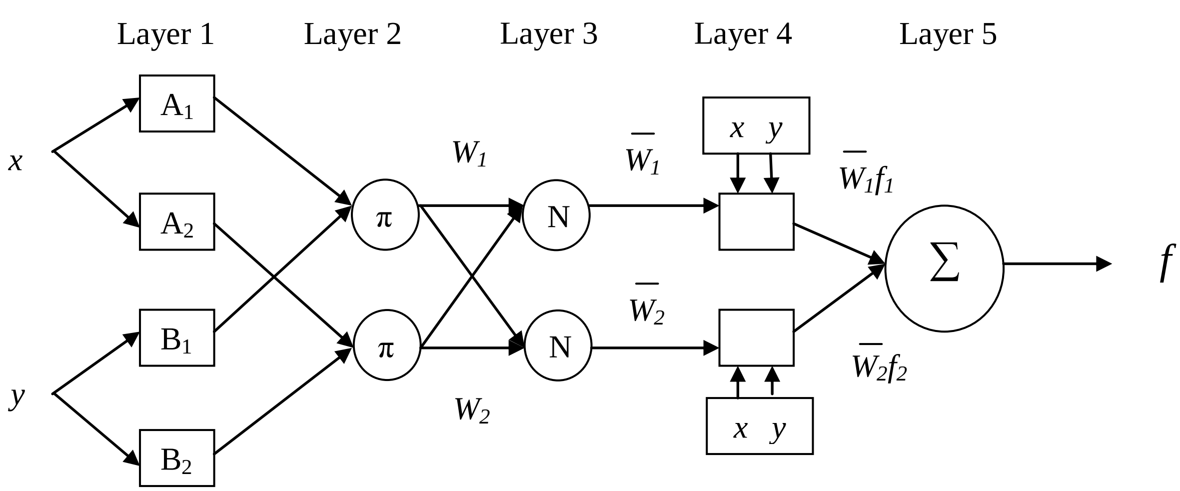


Figure 9. ANFIS algorithm model / architecture

x and y are the input to node i, and A_i and B_i are the linguistic naming such as high, low, medium or small, large, extra large. They are a part of layer 1 (if-part), which relate to the function node. $\mu_{Ai(x)}$ and $\mu_{Bi-2(y)}$ can use different kinds of fuzzy membership functions. For example, a bell-shaped function can be implemented with equation (4) or (5). While the effects of changing parameters {a, b, c} can seen again in [57].

$$\mu_{\mathrm{Ai}}(x) = \frac{1}{1 + \left[\left(\frac{x - \mathrm{c_i}}{\mathrm{a_i}} \right)^{2b_i} \right]}, i = 1,2 \tag{4}$$

or the use of Gaussian membership function in equation (5),

$$\mu_{\mathrm{Ai}}(x) = \exp\left[- \left(\frac{x - \mathrm{c_i}}{\mathrm{a_i}} \right)^2 \right] \tag{5}$$

A_i, B_i, C_i are the parameters of the membership functions. The nodes which are contained in layer 2 is fixed node. Inside this layer there is a fuzzy operator. Layer 2 and 3 consist of the rules and normalization. Fuzzy operator is used to perform fuzzification operation. The input is represented in the form of π, means that the input is considered as a simple multiplier. The output of the layer can be represented as equation (6).

$$O_{2,i} = w_i = \mu_{Ai}(x) * \mu_{Bi}(y),\ i = 1,2 \tag{6}$$

Equation (5) is named as additional reinforcement for the rules. In the layer 3, the nodes are also fixed nodes that are labeled with N, N plays role as a normalization of the previous layer. The output of layer 3 is represented by the equation (7).

$$O_{3,i} = \tilde{\omega}_i = \left(\frac{\omega_i}{\omega_1 + \omega_2} \right), i = 1,2 \tag{7}$$

The fourth layer or also called the then-part layer, contains adaptive nodes. The output of each node in this layer is a multiplier of the normalized firing strength and a first order polynomial. The output of this layer is represented by the equation (8).

$$O_{4,i} = \tilde{\omega}_i f_i = \tilde{\omega}_i (p_i x + q_i y + r_i), \qquad i = 1,2 \tag{8}$$

$\tilde{\omega}$ is the weight of the output of the third layer, p_i, q_i, and r_i which are parameters. In the fifth layer, there is only one fixed node with the name of Σ, this node acts as a summation of all input coming which is represented in the equation (9).

$$O_{5,i} = \sum \tilde{\omega}_i f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i}, \tag{9}$$

Hybrid Learning Algorithm

Learning algorithm which is used in the ANFIS is a combination of gradient descent method and least squares method. In the forward pass of the hybrid learning algorithm, the output node will run forward until it reaches fourth layer and the parameters will be determined using the least square algorithm. In the backward pass, error markers will propagate backward, and the premise parameters are updated using a gradient descent method. Hybrid learning approach can be used to find a convergent point faster than the back propagation method. The output of the hybrid algorithm can be represented in equation (10),

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2$$

$$f = \tilde{\omega}(p_1 x + q_1 y + r_1) + \tilde{\omega}(p_2 x + q_2 y + r_2)$$

$$f = (\tilde{\omega}_1 x) p_1 + (\tilde{\omega}_1 y) q_1 + (\tilde{\omega}_1) r_1 + (\tilde{\omega}_2 x) p_2 + (\tilde{\omega}_2 y) q_2 + (\tilde{\omega}_2) r_2 \tag{10}$$

p_1,q_1, r_1, p_2, q_2 and r_2 are linear parameters. Least squares method is used to identify the optimal values of all parameters. When the premise parameters are not fixed then the search dimension become larger and consequently through training, convergence can be achieved but slower. The ANFIS algorithm combines the two methods, the method of least square and gradient descent method to solve the problem of search dimensions. Least squared method is used to optimize the consequent parameters. Gradient of descent method is used to perform the optimization of the premise parameters. The output of ANFIS is calculated by using the consequent parameters which are obtained from the forward pass. Output error is used to learn from the premise parameters. The output proves that the hybrid algorithm is more efficient in conducting training in ANFIS system.

IV. TRAFFIC SENSORS RESULTS AND DISCUSSION

i) Experiment Data Gathering Scenario

The data needed, as mentioned before, are obtained from two vehicle detection sensors i.e. CCTV camera and smart phone with VDZ, and one verifier i.e. Twitter. The experiment has also been designed so that all data can be synchronized in term of its time and place. To achieve the data acquisition synchronization, during data retrieval, the sensors and verifier have been located in the same place and at the same time. The experiment has been conducted on a road which has three or more cross over bridges, because we must obtain traffic data conditions of at least three types (low, medium and high traffic).

A road of three cross over bridges has been chosen so that we have no problems in placing our video cameras, depicted in Figure 10. For each overpass chosen, besides a camera, a VDZ longitude and latitude coordinate is also placed there (sent by the server and is saved in the smart phone memory to be used by the agent).

Figure 10. Road map containing the VDZ (smaller circles) route in Warung Jati Barat Street and the location of three cross over bridges/overpasses, in bigger circles (Buncit, Pejaten and SMK57), where the video cameras and the person responsible for tweeting are being placed.

These VDZ are used to detect the vehicle movement and consequently its average speed of our three dedicated vehicles (each carries an agent). In addition to that, one person has been assigned on each overpass to monitor the traffic condition of that section of the road and to tweet this data, in to the Twitter account described before (as a verifier) using a hand phone. Consequently, there are 3 smart phones (GPS enabled) inside three dedicated vehicles and another 3 phones to enter traffic condition in to 3 Twitter accounts.

Distance between the three agent vehicles is designed to be close so that the vehicles can enter VDZ and pass the overpass in a short period of time. When the vehicles have entered VDZ, the agent application (which has been installed in the android – GPS enabled mobile phones), sends the data to our server. To obtain a complete data, the three vehicle-carrying agents drove around (as a cycle) the experimental route several times, as shown again in Figure 10.

ii) Results from Smart phone as traffic sensor

A field test was conducted, on 4th of May 2012, near Kelapa Dua, Tangerang, Banten, West Java to estimate the speed accuracy of the VDZ system in a single smart phone, onboard a vehicle. The result is shown in Table 1, with GT as Ground Truth using speedo meter, recorded on video.

Table 1. GPS speed accuracy field test (4 May 2013)

	GT Speed range					
	0≤v<10 km/hr	**10≤v<20 km/hr**	**20≤v<30 km/hr**	**30≤v<40 km/hr**	**40≤v<50 km/hr**	**50≤v≤65 km/hr**
Sample Quantity	n = 26	n = 18	n = 27	n = 27	n = 31	n = 41
GPS Speed deviation for that range	0 to16.6	0 to 33.8	0 to 45	0 to 49	31.3 to 50	45.1 to 64.4
GPS Average Speed	3.1	13.3	21.8	31.3	41.9	53.4
Median	1.4	11.4	23.8	30.3	42.8	53.5
% GPS Average Speed Deviation	n/a	n/a	n/a	n/a	9.4%	6.9%

The experiment route consisted of a single 3.5 km loop nearby Sekolah Pelita Harapan, Lippo Village and 4 zones were placed evenly on the one-way road about 700m apart. Besides sending VDZ_ID, User_ID, VDZ_name, VDZ_group, data to the server every two seconds via the

CDMA phone network, speed measurement via GPS is displayed (as in Figure 13) on the smart phone, which has been captured using a video camera, located behind the driver's seat, together with the car's speedometer.

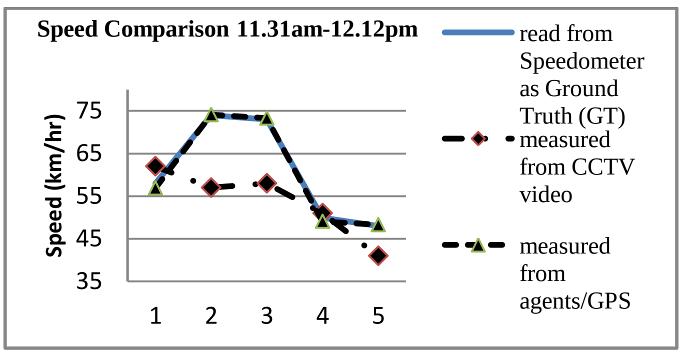
As it can be seen in Table 1 the difference between GPS average speed and its median speed, becomes smaller as it goes to higher speed. In 50≤v≤65 km/hr range the difference is only 0.1, while at the lowest speed range, 0≤v<10 km/hr**,** the difference can be as big as 1.7 km/hr. Nevertheless, in the lowest speed range of 0≤v<10 km/hr, the deviation can be in the range of 0 to16.6 km/hr. The cell with n/a signifies that the speed reading can be showing 0 km/hour in those speed ranges. The result would be better if GPS data is read every second rather than every two seconds, however, it would also drain the smart phone battery faster. One explanation for such a big deviation in low range speed is GPS speed can be read just before the car stops. Consequently, the smart phone will still show the last speed, while as GT, the car has completely stopped. These GPS speed data have been obtained using a CDMA based, hand phone, Samsung Galaxy Young which has cost less than USD100 in mid 2012, purchased in Tangerang. Other phones used in our experiments are Samsung Galaxy Note 1, and Galaxy Tab.

a) b) c)

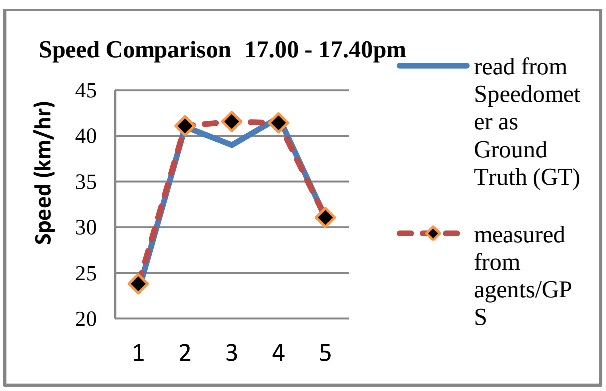
Figure 11. a) the initial menu for VDZ application, as a traffic sensor the agent application, VDZ green circles in b) become red as the car/phone owner passes by the zones. c) shows the direction of agent in the car has travelled which is right to left or 8 to 6. This experiment has been conducted on a target road nearby UI campus, Depok.

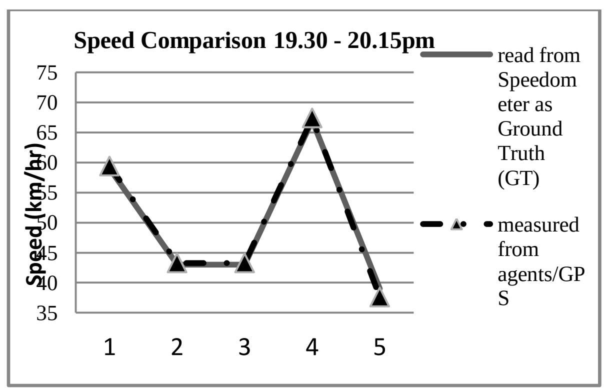
Figure 11 a) shows the initial menu for VDZ application, as a traffic sensor. VDZ green circles in the agent application b) become red as the car of the smart phone owner (see b), passes by the zones. This experiment has been conducted on a target road nearby UI campus, Depok. While c) shows the VDZ_ID given by the server (zones 8, 7, 6 become red after the agent has passed by).

Referring again to Figure 11a-c, the graphic user interface in the mobile VDZ application, is designed so that when the VD circle turns red from green (see second circle from left of b), during the experiment, the driver can confirm via a handy talkie, whether the speed from smart phone is well recorded in the server. We have another person, with a handy talkie, who is monitoring the data in the server concurrently, in a nearby coffee shop.



a)





b) c)

Figure 12. GPS and CCTV speeds are compared with GT in a) while in b) and c) only GPS and GT speeds are obtained because our CCTV system still unable to detect a vehicle in darker surroundings. This experiment was conducted late in the afternoon, while raining and cloudy.

Figure 12a) describes GPS and CCTV speeds, which are compared with GT. While in b) and c) only GPS and GT speeds are obtained because our CCTV system is still unable to detect a vehicle in darker surroundings (close to night time). This experiment was conducted late in the afternoon, while raining and cloudy. As it can be observed, the agent provides a closer agreement to the GT speed records than the extracted speeds from CCTV video images.

Table 2 shows a summary of GPS and CCTV speeds in our Depok experiment. They are compared with GT, to obtain % of accuracy. Note that the average accuracy of VDZ speed is even higher here deviates only by 1, 1.2 and 2.4%, while speed from CCTV is off by 13.4%.

Table 2. Summarized from the Depok experiment GPS and CCTV average speeds are compared with GT, to obtain % of average speed accuracy

	11.31am -12.12pm		**17.00 - 17.40pm**	**19.30 - 20.15pm**
Speed Accuracy Experiment No.	**% of GPS Accuracy**	**% of CCTV Accuracy**	**% GPS Accuracy**	**% GPS Accuracy**
1	98.10	93.10	96.522	99.32
2	99.86	77.03	99.756	99.35
3	99.59	79.45	93.410	99.35
4	98.20	98.00	98.619	99.39
5	99.38	85.42	99.806	96.41
Average Speed Accuracy	**99.03**	**86.60**	**97.623**	**98.76**

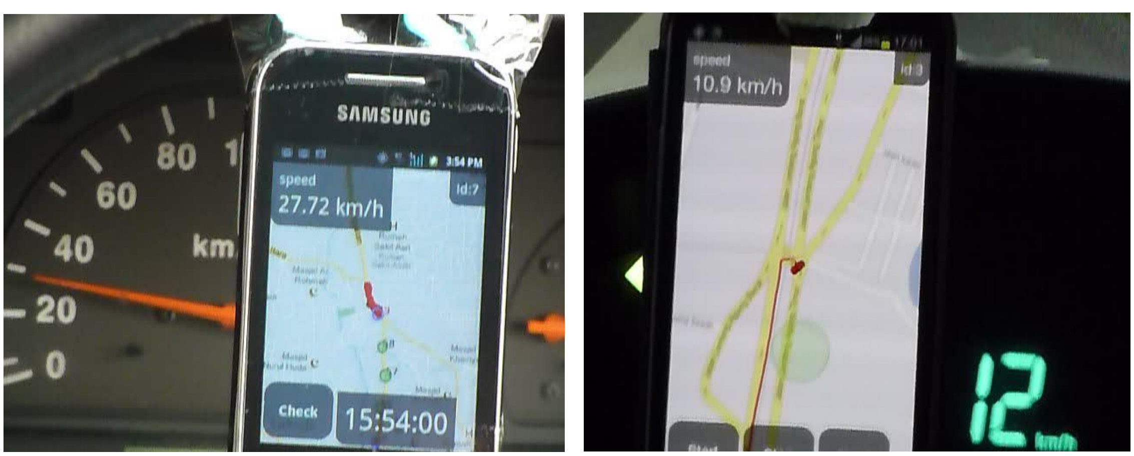


Figure 13. The speeds from GPS data are being compared simultaneously to the speed read from the car’s speedometer as Ground Truth (GT) or alternative reference.

Figure 13 shows the speeds from GPS data which are being compared simultaneously to the speed read from the car's speedometer as Ground Truth (GT) or alternative reference. In the Left side of this figure, analog speedometer (Isuzu New Panther) is presented, showing 29km/hr while the phone displays the agent's speed of 27.7km/hr. In the right, a reading of a digital speedometer, with a value of 12km/hr in a Toyota Vios is shown, while the phone displays 10.9km/hr. It should be noted that they both carry similar accuracy.

iii) Results from CCTV as traffic sensor

Applying OpenCV libraries, the CCTV speed estimation system is developed using C++ as the programming language. In our previous work [31], we adopted the speed calculation of individual vehicle to determine the traffic density of a lane, using computer vision method.

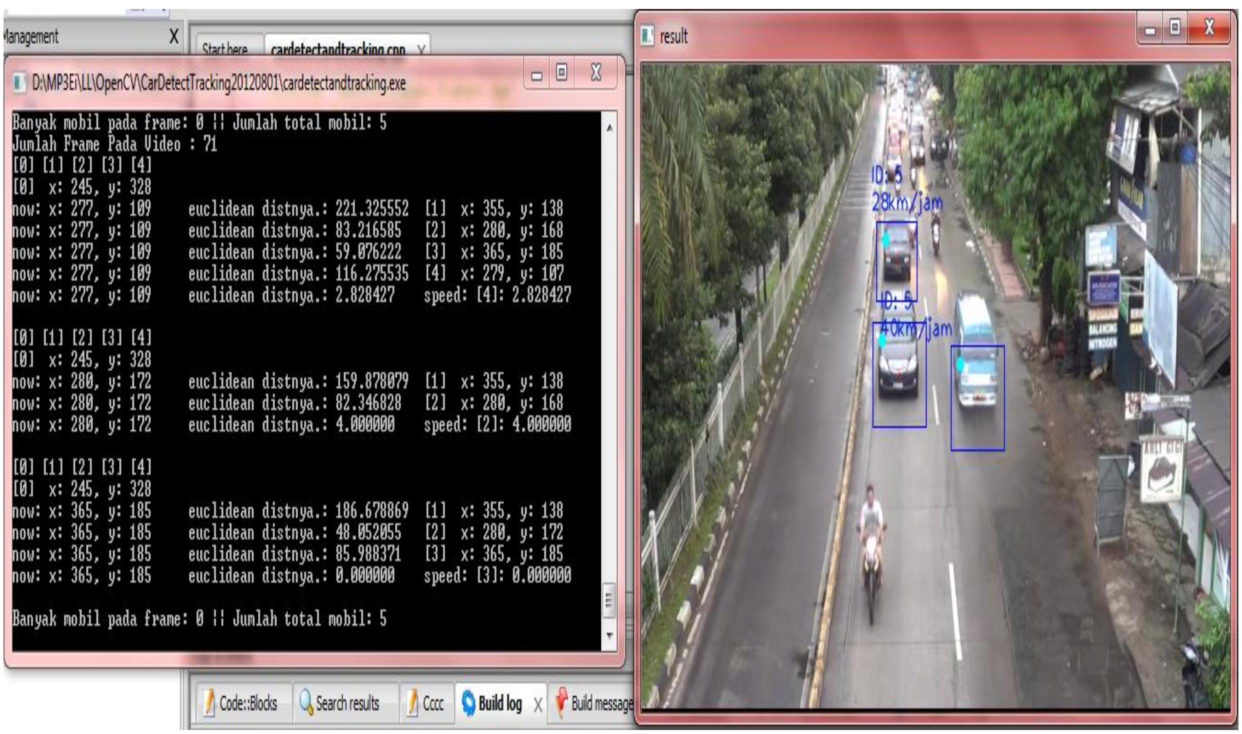


Figure 14. CCTV speed estimation system runs in the background, while vehicles are actually moving in real time

Figure 14 shows the system as it runs the program (see left), it also displays the vehicles (see right) in real time, with different rectangular colour, signifying the state of detection (successful or unsuccessful) and the speed of each passing vehicle in the successful detection state.

Three vehicles are used as agents in this Warung Jati Barat Street experiment (south of Jakarta, Indonesia). The set up can be described, as follows. Three cameras are placed on top of three cross over bridges, to capture the three traffic-street conditions: Low (clear traffic), Medium and High (slow till jammed traffic). They are placed in an orderly manner, in Warung Jati Barat Street. We call them SMK57, Pejaten, and Buncit cross over / pedestrian bridges.

Table 3**.** Summary of experiment result using VDZ, CCTV and Twitter

1	2	3	4	5	6	7	8	9
Exp. Number	**Videos Name**	**Bridge Location**	**Number of Cars in 30 sec period**	**Penetration rate (%)**	**Average Speed from VDZ (Km/hr)**	**Average Speed from CCTV (Km/hr)**	**Actual Time**	**Twitter Condition (Verification)**
Exp. 1 A	Vid_1_A.avi	Buncit	18	16.7	36	73	16:35	Low Traffic
Exp. 1 B	Vid_1_B.avi	Pejaten	13	16.7	17	58	16:41	Low Traffic
Exp. 1 C	Vid_1_C.avi	SMK57	23	13.0	33	39	16:50	Low Traffic
Exp. 2 A	Vid_2_A.avi	SMK57	37	8.1	34	24	16:52	Medium Traffic
Exp. 2 B	Vid_2_B.avi	Pejaten	5	13.0	19	60	16:57	Medium Traffic
Exp. 2 C	Vid_2_C.avi	Buncit	25	8.1	26	18	17:02	Low Traffic
Exp. 3 A	Vid_3_A.avi	Buncit	20	13.0	36	33	17:05	Low Traffic
Exp. 3 B	Vid_3_B.avi	Pejaten	4	8.1	37	21	17:07	Low Traffic
Exp. 3 C	Vid_3_C.avi	SMK57	26	13.0	21	20	17:13	Heavy Traffic

Note: These CCTV data speed values (column 7) seem to be rather a long way off from VDZ data speeds (column 6), this is possible if the video camera is not properly calibrated. But we decided to use them anyway – because we want to find out whether ANFIS can produce a better way in integrating the 3 sources of data.

As mentioned before, three agents are video-recorded over 30 seconds period, to determine the penetration rate (number of agents divided by the total passing cars during that 30 seconds, should be higher than 2%) and thus makes the average speed calculation valid. For example, penetration rate of Exp. 1A (Table 3, second row, fifth column) 16.7 % is obtained from 3/18 (3 is the number of agents, and 18 is the total passing cars during that 30 seconds).

The average speed from CCTV data is shown in Table 3, column 7, and it is obtained by summing all the individual speeds of each agent divided by the number of agents during that 30 seconds period. Similarly, the average speed from VDZ in Table 3, column 6, is shown next to penetration rate data, column 5.In our previous research [47], [48], [58], we also used this kind of environment to detect and track vehicles.

A B C

Figure 15. Sample of Average Speed Estimation of CCTV from Experiment 1

Our previous research has provided an algorithm to count the number of passing vehicles. This extracted speed data from CCTV, will then be used as one of the features in determining the traffic condition in that lane. Figure 15 A-C shows three snapshots depicting our experiment in Warung Jati Barat Street, using video cameras. The focus of this CCTV research is to know the speed and number of cars passing in that period.

iv) Further Data Processing

In this paper, we propose to use a neural network algorithm to determine the traffic condition based on the original data that we have collected.

A. CCTV / Video Camera

Video cameras have recorded the traffic state from the bridge, and at the same time the agents carried by our cars, have passed through the areas of VDZ, around the same circuit for three times. The data which is obtained from the processed video footage is shown in Table 3, column 7.

B. Mobile Agent in smart phones and Application Server

Agents in this study is equipped with a custom-made mobile applications which is originally developed by the researchers, this application will automatically transmit navigation data from the agent when the agent is located in the VDZ.

There are two applications that are embedded in this study, the first application is a mobile agent application and the second application is a web service server application. The workings of the two applications are as follow:

1. Mobile application has a role in detection of vehicle speed when passing through the VDZ.

Table 4. VDZ Data along with Time stamp, agent ID and speed.

No.	**Time Stamp**	**VDZ ID**	**Location**	**VDZ Area**	**Agent ID**	**Speed (Km/h)**
1	May 11, 2013, 4:35:37	49	jembatan 4 mampang	Mampang	3	37.76
2	May 11, 2013, 4:35:36	49	jembatan 4 mampang	Mampang	3	40.85
. . .	. . .	. . .	. . .	. . .	. . .	. . .
63	May 11, 2013, 5:13:36	46	jembatan 1 mampang	Mampang	8	20.23

2. The agent (in smart phone) sends the vehicle speed data to be stored in the server. The data is sent to the mobile agent server, and consists of 6 fields:

Timestamp	VDZ ID	VDZ Name	VDZ Group	Android ID	Speed

Legend :

Timestamp : Time of the event

VDZ ID : ID Number of VDZ

VDZ Name : the name of a street section say, Pejaten

VDZ Group : VDZ Group is a collection of a number of VDZ located within a road.

Android ID : Mobile Device ID

Speed : The speed of the vehicle which carries by the mobile phone, calculated from GPS data

3. Web service application will receive the data from the entire mobile application and store it into a database. Table 4 shows a sample of 63 records of collected data from VDZ traffic sensor.

C. Twitter

Twitter is used as a data verifier for the current state of traffic in the designated areas or VDZ. In this case we use 3 volunteers to tweet, in order to simulate the Twitter police accounts officer, and place these volunteers in the assigned cross over bridges.

Table 5. Extracted Twitter Data

Tweet Time	**Tweet ID**	**Tweet contents**	**Twitter Account**
16:35:38	333153	Traffic flow buncit indah to warung jati low traffic	lab_1231_3
16:40:07	333155	Traffic flow from buncit heading to pejaten in low traffic	sibifasilkom
16:50:48	333157	Traffic flow from pejaten heading to smk57 in low traffic	lab_1231_2
16:53:08	333158	Traffic flow from deptan heading to smk57 in medium traffic	lab_1231_2
16:58:26	333159	Traffic flow from smk57 heading to pejaten02 in medium traffic	sibifasilkom
17:02:08	333160	Traffic flow buncit indah1 to warung jati1 low traffic	lab_1231_3
17:06:06	333161	Traffic flow warung jati2 to buncit indah2 low traffic	lab_1231_3
17:06:00	333161	Traffic flow from buncit02 heading to pejaten in low traffic	sibifasilkom
17:06:40	333164	Traffic flow from pejaten heading to smk57 in high traffic	lab_1231_2

These “police officers” manually type the traffic state in assigned spots. For example their tweets are as the following:

"Traffic condition from SMK57 heading to pejaten in low traffic condition"

It means that the traffic condition of VDZ SMK 57 towards VDZ pejaten, is in low traffic condition. The volunteer tweets every time the agent is passing an assigned spot. The twitter data extraction results are described in Table 5. Every tweet should be the representation of the traffic state in each VDZ.

v) The Use Of Adaptive Neuro Fuzzy Inference System To Classify Traffic Conditions

In this section, we present the data integration process of two different sensors (VDZ and CCTV), as well as Twitter data as traffic verifier.

A. Traffic state classification using VDZ Data

VDZ Data have some parameters that can be used as an input feature for ANFIS algorithm. The collected parameters from the experiments are: the Timestamp, VDZ ID, Location, VDZ spot, Agent ID, and Agent's speed. Among those five parameters we have chosen Agent's speed as the only input and the output features, such as traffic conditions is obtained from twitter. The main reason that we have chosen the Agent's speed as input feature is because we can extract the traffic state condition at the same time of the vehicle movement, so that the input feature can either represent the state of traffic or speed at any given time. Each input feature (VDZ agent's speed) is attached to the output presumably written by our volunteer using twitter. In order to fit the data between the input feature and output, we have applied timestamp equalization feature to input the data containing the agent's speed on the server and timestamp on twitter social media. The data representation of the input and output features are described in
Table 6.

Table 6. Combined Input Feature (VDZ) and Output Representation (Twitter)

No.	Input Feature	Output
	VDZ Sensor **VDZ Speed (Km/h)**	**Twitter Traffic Condition Verifier**
1	37.76 km/h	Low Traffic
2	40.85 km/h	Low Traffic
. . .	. . .	. . .
63	20.23 km/h	High Traffic

We have tested this integrated system using cross validation of 90% of the data, as data train, and the rest 10% is used for data testing. All data that we have collected is 67 records, which contain all the three traffic states, including VDZ and CCTV speed data. While for data training we use 57, and 6 data for data testing. The selection of the data testing is done by selecting the appropriate amount of data representative of each class in the data (low traffic, medium traffic, and high traffic).

Cross validation test was performed 10, 100, and 1000 times. The calculations performed in the cross validation test are: MAE (Mean Average Error), MSE (Mean Square Error), and RMSE (Root Mean Square Error). MAE, MSE, and RMSE basically calculate the difference between the results obtained from error prediction system with the actual output data. Representation of MAE, MSE, and RMSE are described consecutively, in equations (11)-(13),

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{N} |\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}|, \tag{11}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{j=1}^{N} |\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}|^2, \tag{12}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{N} |\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}|^2}, \tag{13}$$

$\mathrm{y_i}$ is the original data and $\hat{\mathrm{y}}_\mathrm{i}$ is the output of the classification system. In this study we perform simulation as many as 10, 100, and 1000 times. The large amount of the experiment is intended to make sure that error remains constant as the number of experiment is increased. The cross validations results of 10 iterations, for single and combined input parameters, are presented in Table 8.

Cross validations experiments, which have produced MAE, MSE, and RMSE using single VDZ input and Twitter output, have shown bigger error (Table 8 a) than a combined version (Table 8 b, this is presented in the next sub section). This is expected, since the “values” of Twitter data has come from human observations, while VDZ speed has come from GPS data, which gives more accurate values, so it obvious comparing between the two of them will produce bigger error, than the combined one.

The greatest error rate representation for 10 trials of MAE for single VDZ input parameter is 0.59 and the smallest MAE value is 0.38. These results are presented in Table 8 a, column 2. While the average error rate resulting from the whole experiment is 0.48. The experiments are performed 10 times, 100 times, and 1000 times. The error rate representation up to 1000 trials (MAE) is represented in Figure 17 a.

B. Traffic state classification using data from VDZ and CCTV

VDZ data has become the input feature is the agent's speed, and the extracted data from CCTV data, is the average speed of a vehicle within a period of thirty seconds.

While the number of vehicles which has appeared in the recorded video, for thirty seconds has become the traffic volume giving 3 possible traffic states: low, medium and high traffic. The combined input feature and output representation is depicted in Table 7.

Table 7. Combined Input Features (VDZ & CCTV) and Output Representation (Twitter)

	Input Features			**Output**
	VDZ Sensor	**CCTV Sensor**		**Twitter Verifier**
No.	Speed from VDZ (Km/h)	Speed from CCTV (Km/h)	Amount of Cars	Traffic Condition
1	37.76 km/h	73 km/h	18 cars	Low Traffic
2	40.85 km/h	58 km/h	13 cars	Low Traffic
. . .	. . .	. . .	. . .	. . .
63	20.23 km/h	26 km/h	20 cars	High Traffic

One of the reasons we use ANFIS method in determination of traffic state conditions is because traffic state conditions do not have the right model, for each condition. We expect by using the ANFIS method, we have the right model for every traffic state conditions.

Figure 16 represents the membership function of each input feature (VDZSpeed, CCTVSpeed, and AmountofCars). The input Features will form the fuzzy rules to generate traffic conditions such as low traffic, medium traffic, and high traffic.

The way of testing this automatic error estimation prediction system is performed by using cross validation of 63 data that we have collected and combined. 90% would be act as training data and 10% of the data become testing data. We use 57 data for training, and 6 data for testing.

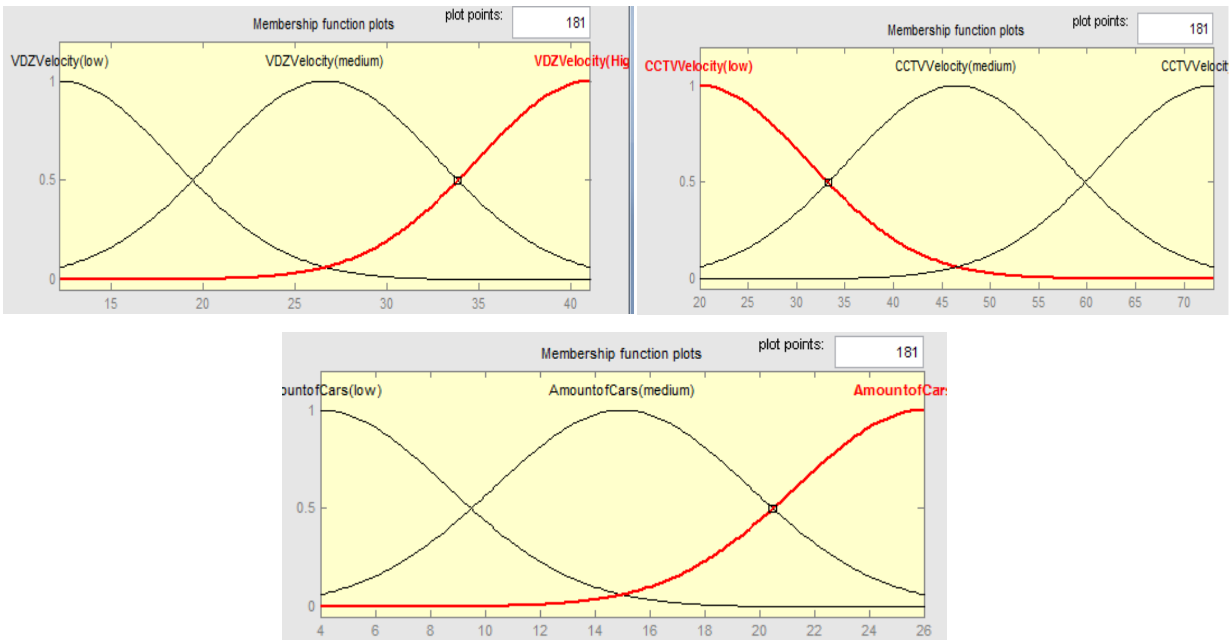


Figure 16. (a). Membership Function VDZSpeed, (b). Membership Function CCTVSpeed, (c). Membership Function Amount of Cars

The selection of the data testing is done by selecting the appropriate amount of data representative of each class in the data. Cross validation scenario test is performed as the same as those performed on cross validation tests using VDZ data.

All cross validation experiments produce MAE, MSE, and RMSE using the combined data. From the MAE, MSE, and MSE simulations, we can say that the predicted error becomes much smaller than the experiment using only the VDZ data as input and Twitter as output Figure 17, as shown in Table 8.

The greatest error rate representation for 10 trials of MAE for combined input parameters is 8.8 x 10^{-4} and the smallest number of MAE is 1.4 x 10^{-4}, while the average error rate resulting from the whole experiment is 1.8 x 10^{-4} (see Table 8 b, column 2).

The experiments are performed up to 1000 times. The representation of the error rate (MAE) for 1000 trials, for this combined version, is shown in Figure 17 b.

Comparison of MAE between Figure 17 a and b shows that the combination of VDZ and CCTV as input parameters, produces less error rate.

Table 8. MAE, MSE, and RMSE results for 10 times experiment using a) single VDZ input only, and b) combined input (VDZ and CCTV as input), both using Twitter as verifier (output)

Result of single VDZ input only			
No.	**MAE**	**MSE**	**RMSE**
1	0.592409	0.449852	0.670710
2	0.478459	0.392094	0.626174
3	0.422615	0.318065	0.563973
4	0.383059	0.289650	0.538191
5	0.459461	0.326165	0.571109
6	0.475297	0.360194	0.600161
7	0.536546	0.455813	0.675139
8	0.430477	0.318459	0.564322
9	0.467605	0.357008	0.597501
10	0.518848	0.394712	0.628261

Result of combined input (VDZ & CCTV)			
No.	**MAE**	**MSE**	**RMSE**
1	0.00014135	0.00000003	0.00017247
2	0.00029212	0.00000013	0.00036085
3	0.00059405	0.00000095	0.00097695
4	0.00088173	0.00000222	0.00148862
5	0.00078601	0.00000115	0.00107262
6	0.00049615	0.00000045	0.00066729
7	0.00061429	0.00000081	0.00089924
8	0.00054277	0.00000096	0.00097987
9	0.00038601	0.00000022	0.00046528
10	0.00080543	0.00000208	0.00144219

We can see the average number of MAE, for single input parameter (VDZ) is equal to 0.48 (Figure 17 a), and the test results of combined input parameters VDZ and CCTV have produced a much smaller average MAE of 5.1 x 10^{-4}, as represented Figure 17 b.

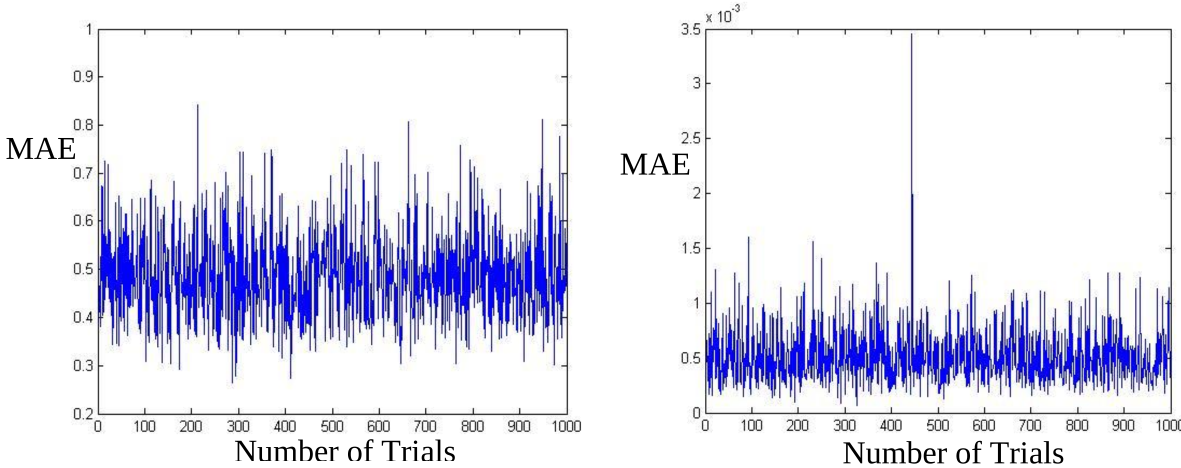


Figure 17. a) MAE (VDZ Data), b) MAE (VDZ and CCTV Data)

Figure 17 represents a significant error difference or in other words, the average error generated by merging the data VDZ and CCTV is much smaller than the average error generated by the data VDZ only. The addition of CCTV data to VDZ is one way to increase accuracy as well as the reduction of error rate compared to using only the VDZ data speed.

However, this does not mean that VDZ data is of lower accuracy than CCTV and Twitter. This experiment only shows that by using ANFIS the impact of a big error in one data source can be reduced, by considering data from another source. In this case we know that the data speed from CCTV, is very different to the VDZ speed, in Warung Jati Barat Street experiment, due to lack of camera calibration in our experiment. Our Ground Truth comparison experiments have shown that VDZ speed data has much lower error than the data speed obtained from CCTV. Consequently, ANFIS shows that if both sources of data are in big error (i.e. speed from CCTV and Twitter traffic state) then the more accurate data (i.e. VDZ) will be deemed not accurate enough, which is an unavoidable weakness. The good news is that worst scenario is most unlikely to happen, and ANFIS can make our system more accurate, when VDZ data and CCTV data are in a closer agreement.

VI. CONCLUSIONS

A number of experiments have been conducted for this research, and it has been found that Virtual Detection Zone (VDZ) method has been able to match the correct road by comparing current location data in the GPS enabled phone with a set of pre-determined check points (circular VDZ, successfully giving consistent results with a radius of 100m). It is also able to provide traffic data speed in the accuracy range of 93.4% to 99.9% in higher speed range (50 to 65 km/hour) and able to detect lower speeds in range of 0 to 20 km/hour. VDZ only needs one longitude and latitude coordinate, to be able to form a detection aware zone. Furthermore, we have shown from experiments that in our integrated ITS, by using Adaptive Neuro Fuzzy Inference System our speed data from video images captured from CCTV and extracted traffic states from simulated police Twitter, along with VDZ data speed can be better classified to obtain a more accurate traffic conditions.

REFERENCES

[1] G. Leduc, “Road Traffic Data : Collection Methods and Applications,” Luxembourg, 2008.

[2] U.S. Dept of Transportation and U. S. D. of Transportation, *Traffic Detector Handbook : Third Edition-Volume I*, 3rd ed., vol. I, no. October. Springfield, VA, 22161 and Research and Technology Product Distribution Center, 9701 Philadelphia Court, Unit Q, Lanham, MD: Research, Development, and Technology Turner-Fairbank Highway Research Center,, 2006, pp. 1–291.

[3] U. S. D. of Transportation, *Traffic Detector Handbook : Third Edition-Volume II*, Third. Springfield, VA, 22161 and Research and Technology Product Distribution Center, 9701 Philadelphia Court, Unit Q, Lanham, MD: Research, Development, and Technology Turner-Fairbank Highway Research Center,, 2006, pp. 1–396.

[4] Z. Chen and T. Ellis, “Multi-shape Descriptor Vehicle Classification for Urban Traffic,” *2011 International Conference on Digital Image Computing: Techniques and Applications*, pp. 456–461, Dec. 2011.

[5] A. Viloria, M. Gonzalo-Tasis, R. Martinez, L. M. Fuentes, and J. Finat, “Mobile Voronoi Diagrams for Traffic Monitoring under Bad Visibility Conditions,” *2011 Eighth International Symposium on Voronoi Diagrams in Science and Engineering*, pp. 228–233, Jun. 2011.

[6] D. J. Dailey, F. W. Cathey, and S. Pumrin, “An algorithm to estimate mean traffic speed using uncalibrated cameras,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 1, no. 2, pp. 98–107, Jun. 2000.

[7] L. Grammatikopoulos, G. E. Karras, and E. Petsa, "Geometric Information From Single Uncalibrated Images Of Roads," in *International Archives of Photogrammetry & Remote Sensing*, 2002, vol. 34, no. 5, pp. 21–26.

[8] F. W. W. Cathey and D. J. J. Dailey, "A Novel Technique to Dynamically Measure Vehicle Speed using Uncalibrated Roadway Cameras," in *IEEE Proceedings. Intelligent Vehicles Symposium, 2005.*, 2005, no. 2, pp. 777–782.

[9] L. Grammatikopoulos, G. Karras, and E. Petsa, "Automatic Estimation Of Vehicle Speed From Uncalibrated Video Sequences," in *International Symposium On Modern Technologies, Education And Professional Practice In Geodesy And Related Fields*, 2005, no. 2003, pp. 3–4.

[10] C. Maduro, K. Batista, P. Peixoto, and J. Batista, "Estimation Of Vehicle Velocity And Traffic Intensity Using Rectified," Coimbra, Portugal, 2008.

[11] C. Maduro, K. Batista, and J. Batista, "Estimating Traffic Intensity Using Profile Images On Rectified Images," in *ISR-Institute of Systems and Robotics*, 2009, pp. 1149–1152.

[12] G. Garibotto, P. Castello, E. Del Ninno, P. Pedrazzi, and G. Zan, "Speed-vision: speed measurement by license plate reading and tracking," *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No.01TH8585)*, pp. 585–590, 2001.

[13] T. Pai, W. Juang, and L. Wang, "An adaptive windowing prediction algorithm for vehicle speed estimation," *ITSC 2001. 2001 IEEE Intelligent Transportation Systems. Proceedings (Cat. No.01TH8585)*, pp. 901–906, 2001.

[14] T. N. Schoepflin, D. J. Dailey, and S. Member, "Dynamic Camera Calibration of Roadside Traffic Management Cameras for Vehicle Speed Estimation," *IEEE Transactions On Intelligent Transportation Systems*, vol. 4, no. 2, pp. 90–98, 2003.

[15] X. He and N. C. Yung, "A Novel Algorithm for Estimating Vehicle Speed from Two Consecutive Images," *2007 IEEE Workshop on Applications of Computer Vision (WACV '07)*, pp. 12–12, Feb. 2007.

[16] T. N. Schoepflin, D. J. Dailey, and S. Member, "Algorithms for Calibrating Roadside Traffic Cameras and Estimating Mean Vehicle Speed," in *Proceedings of the 2007 IEEE Intelligent Transportation Systems Conference*, 2007, pp. 277–283.

[17] S. K. Endarnoto, S. Pradipta, A. S. Nugroho, and J. Purnama, "Traffic Condition Information Extraction & Visualization from Social Media Twitter for Android Mobile Application," in *International Conference on Electrical Engineering and Informatics*, 2011, no. July, pp. 1–4.

[18] B. S. R. B. J. Singh, "Real Time Prediction of Road Traffic Condition in London via Twitter and Related Sources by," Middlesex University, 2012.

[19] A. Wibisono, I. Sina, M. A. Ihsannuddin, A. Hafidz, B. Hardjono, and P. Mursanto, "Traffic Intelligent System Architecture Based on Social Media Information," in *ICACSIS*, 2012, pp. 25–30.

[20] R. Kosala and E. Adi, "Harvesting Real Time Traffic Information from Twitter," in *Procedia Engineering*, 2012, vol. 50, no. Icasce, pp. 1–11.

[21] M. Berman, "Cell Phone Location System," Tallahassee, 2007.

[22] J. Kim, "Energy-Efficient Rate-Adaptive GPS-based Positioning for Smartphones," in *MobiSys*, 2010, pp. 299–314.

[23] J. C. Herrera, D. B. Work, R. Herring, and X. Jeff, "Evaluation of Traffic Data Obtained via GPS-enabled Mobile Phones : the Mobile Century field experiment," in *Transportation Research*, 2009, no. June, pp. 1–30.

[24] B. Hoh, T. Iwuchukwu, Q. Jacobson, D. Work, A. M. Bayen, R. Herring, J. C. Herrera, M. Gruteser, M. Annavaram, J. Ban, I. C. Society, and S. Member, "Enhancing Privacy and Accuracy in Probe Vehicle-Based Traffic Monitoring via Virtual Trip Lines," *IEEE Transactions On Mobile Computing*, vol. 11, no. 5, pp. 849–864, 2012.

[25] K. Yadav, V. Naik, P. Singh, A. Singh, and P. Range, "Alternative Localization Approach for Mobile Phones Without GPS," in *ACM*, 2010, pp. 1–4.

[26] "Privacy Policy (Google's)." [Online]. Available: http://www.google.com/policies/privacy/. [Accessed: 10-Jan-2013].

[27] B. Schwartz, "How Does Google's Predictive Traffic Maps Work?," *Search Engine Round Table*, 2010. [Online]. Available: http://www.seroundtable.com/archives/023155.html. [Accessed: 21-Jan-2013].

[28] S. Cheung, "Traffic Surveillance by Wireless Sensor Networks : Final Report," Berkeley, 2007.

[29] B. Hardjono, A. Nurhadiyatna, P. Mursanto, and W. Jatmiko, "Development of Traffic sensor system with Virtual Detection Zone," in *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 2012, pp. 19–23.

[30] B. Hardjono, A. Wibowo, M. F. Rachmadi, and W. Jatmiko, "Mobile phones as traffic sensors with map matching and privacy considerations," in *Micro-Nano Human Science (MHS)*, 2012, pp. 450–455.

[31] A. Nurhadiyatna, B. Hardjono, A. Wibisono, W. Jatmiko, and P. Mursanto, "ITS Information Source : Vehicle Speed Measurement Using Camera as Sensor," in *ICACSIS*, 2012, pp. 191–196.

[32] V. Jain, A. Sharma, and L. Subramanian, "Road Traffic Congestion in the Developing World," in *ACM Computer for Development*, 2012, p. 10.

[33] Q. Bai, T. Carrato, C. M. Laffoon, D. M. Mourad, P. Nesbitt, J. L. Ryan, L. Zhang, and V. Srikanth, "Integrate traffic data with IBM Intelligent Transportation using a traffic data gateway Meet the challenges of today's traffic raw data collection from detectors embedded in roadway infrastructures," 2011.

[34] X. Xiaobin, Z. Zhe, and W. Chenglin, "Data Fusion Algorithm Of Fault Diagnosis," *International Journal On Smart Sensing And Intelligent Systems*, vol. 6, no. 1, pp. 171–190, 2013.

[35] M. Valera and S. A. Velastin, "Intelligent distributed surveillance systems : a review," *IEE Proc.-Vis. Image Signal Process*, vol. 152, no.2, no. 20041147, pp. 192–204, 2005.

[36] U. Park, F. Silva, G. Guiliano, M. Hou, J. Heidemann, and X. Wang, "Single- and Multi-Sensor Techniques to Improve Accuracy of Urban Vehicle Classification," in *ISI-TR*, 2006, p. 13.

[37] W. Jatmiko, A. Azurat, A. Wibowo, H. Marihot, and M. Wicaksana, "Self-Organizing Urban Traffic Control Architecture With Swarm-Self Organizing Map In Jakarta : Signal Control System And Simulator," *International Journal On Smart Sensing And Intelligent Systems*, vol. 3, no. 3, p. 23, 2010.

[38] S. Jain, R. K. Ghosh, and R. K. Shyamsundar, "Engineering Location Based Pathfinding on Indian Road Networks Over Low End Mobile Phones," *IEEE*, pp. 1–9, 2010.

[39] B. Hoh, M. Gruteser, H. Xiong, S. Member, and A. Alrabady, "Achieving Guaranteed Anonymity in GPS Traces via Uncertainty-Aware Path Cloaking," *IEEE Transactions On Mobile Computing*, vol. 9, no. 8, pp. 1089–1107, 2010.

[40] B. Hoh, M. Gruteser, R. Herring, J. Ban, D. Work, J. Herrera, and A. M. Bayen, "Virtual Trip Lines for Distributed Privacy-Preserving Traffic Monitoring," in *ACM MobiSys*, 2008, pp. 15–28.

[41] R. D. Haney, "Location sharing and tracking using mobile phones or other wireless devices," 7353034 B22008.

[42] A. Demers, G. F. List, W. A. Wallace, E. E. Lee, and J. M. Wojtowicz, "Probes as Path Seekers: A New Paradigm," *Journal of the Transportation Research Board*, 2006. [Online]. Available: http://trb.metapress.com/content/e3u6163h011t6684/.

[43] B. Zan, P. Hao, M. Gruteser, and X. Ban, "VTL Zone-Aware Path Cloaking Algorithm," in *International IEEE Conference on Intelligent Transportation Systems*, 2011, pp. 1525–1530.

[44] D. B. Work, O. Tossavainen, Q. Jacobson, A. M. Bayen, A. Smartphones, and L. Sensors, “Lagrangian Sensing : Traffic Estimation with Mobile Devices,” *Proceedings of the 2009 American Control Conference St. Louis*, 2009.

[45] A. M. P. . Bayen, “Collecting 2008 Traffic Data from GPS-Equipped Cell Phones.” .

[46] S. Amin, S. Andrews, S. Apte, J. Arnold, J. Ban, M. Benko, A. M. Bayen, B. Chiou, C. Claudel, C. Claudel, T. Dodson, O. Elhamshary, Batina, Gruteser, Herrera, Herring, Hoh, Jacobson, Kumar, Iwuchukwu, Lew, Litrico, and Luddington, “Mobile Century Using GPS Mobile Phones as Traffic Sensors : A Field Experiment,” in *15th World Congress on Intelligent Transportation Systems*, 2008, pp. 8–11.

[47] M. F. Rachmadi, F. Al Afif, W. Jatmiko, P. Mursanto, E. A. Manggala, M. A. Ma’sum, and A. Wibowo, “Adaptive traffic signal control system using camera sensor and embedded system,” in *TENCON 2011 - 2011 IEEE Region 10 Conference*, 2011, pp. 1261–1265.

[48] F. Al Afif, M. F. Rachmadi, W. Jatmiko, and P. Mursanto, “Enhanced Adaptive Traffic Signal Control System Using Camera Sensor and Embedded System,” in *MHS*, 2011, pp. 367–372.

[49] “Traffic Management Center,” 2013. [Online]. Available: http://www.tmcmetro.com/profil/traffic-management-center. [Accessed: 10-Jan-2013].

[50] P. Viola and M. Jones, “Rapid object detection using a boosted cascade of simple features,” in *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, 2001, vol. 1, pp. I–511–I–518.

[51] G. Welch and G. Bishop, “An Introduction to the Kalman Filter,” 2006.

[52] N. Buch, S. a. Velastin, and J. Orwell, “A Review of Computer Vision Techniques for the Analysis of Urban Traffic,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 3, pp. 920–939, Sep. 2011.

[53] I. M. A. Setiawan, E. M. Imah, and W. Jatmiko, “Arrhytmia Classification using Fuzzy-Neuro Generalized Learning Vector Quantization,” in *ICACSIS*, 2011, pp. 978–979.

[54] J. R. Jang, “ANFIS : Adaptive Network-Based Fuzzy Inference System,” *IEEE Transactions On Systems, Man, And Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.

[55] H. Yan, Z. Zou, and H. Wang, “Adaptive neuro fuzzy inference system for classification of water quality status,” *Journal of Environmental Sciences*, vol. 22, no. 12, pp. 1891–1896, Dec. 2010.

[56] L. A. Zadeh, “Fuzzy Sets,” *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.

[57] P. P. Bonissone, “Adaptive Neural Fuzzy Inference Systems (ANFIS): Analysis and Applications,” 2002.

[58] B. Zaman, W. Jatmiko, A. Wibowo, E. M. Imah, U. Indonesia, N. Science, and U. N. Surabaya, “Implementation Vehicle Classification On Distributed Traffic Light Control System Neural Network Based,” in *ICACSIS*, 2011, pp. 978–979.