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An inference engine for smartphones to preprocess data and detect stationary and transportation modes

Hamid Reza Eftekhari [a], Mehdi Ghatee [a,b,*]

[a] Department of Computer Science, Amirkabir University of Technology, N. 424, Hafez Avenue, Tehran 15875-4413, Iran
[b] Intelligent Transportation Systems Research Institute, Amirkabir University of Technology, Tehran, Iran

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ABSTRACT

A smartphone can be utilized as a cost-effective device for the purposes of intelligent transportation system. To detect the movement and the stationary statuses in the motorized and non-motorized modes, this study develops a new inference engine, including two sets of rules. The first sets of rules are defined by the related thresholds on the features of smartphone sensors while the second sets are extracted from the human knowledge to improve the results of the first rules. The experimental results reveal that by utilizing Inertial Measurement Unit (IMU) sensors in the proposed inference engine, it is possible to save 40% energy in comparison with the previous research. Moreover, this engine increases the accuracy of the motorized mode detection to 95.2% and determines the stationary states in motorized mode with 97.1% accuracy.

1. Introduction

The ability of smartphones to recognize driver behavior encourages researchers to analyze the data provided by smartphone sensors for Intelligent Transportation Systems (ITS). Zhang et al. (2010) used the data generated by smartphones to recognize driver behavior, Bhoraskar et al. (2012) and Eriksson et al. (2008) used it to detect road abnormalities, Mohan et al. (2008) to monitor traffic, and White et al. (2011) to detect accidents. A drawback to these approaches is that a great deal of smartphone data concerns time intervals for which the driver is outside of the vehicle. These parts are not useful for ITS applications and their storage and processing are expensive and may cause false detection. On the other hand, the use of smartphones in some ITS applications requires prepossessing to detect whether or not the smartphone is inside a vehicle. This prepossessing phase must be done continuously over the course of a day (Ghorpade et al., 2015). For example, for accident detection, road surface classification, and connection between on-board devices and drivers, such preprocessing is important.

To respond to this need, the present study developed a method of recognizing the motorized mode independent of motorized mode and traffic conditions. Good accuracy and low energy consumption are two important properties of this solution. Because other solutions based on GPS consume a large amount of energy and their accuracy is dependent on the environment, it is reasonable to search for better alternatives to GPS sensors. Previous techniques independent of GPS (or Wi-Fi) suffer from low accuracy. Major efforts in this area have been reviewed by Engelbrecht et al. (2015) and Hoseini-Tabatabaei et al. (2013).

* Corresponding author at: Department of Computer Science, Amirkabir University of Technology, N. 424, Hafez Avenue, Tehran 15875-4413, Iran.
E-mail address: ghatee@aut.ac.ir (M. Ghatee).

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Table 1 compares recent literature on smartphone-based systems in transportation concepts. The determination of smartphone location and scientific gaps in the methods are presented based on application category. The similarity of sensor data for motorized and non-motorized modes, particularly under stop and continual stop-and-go conditions, and the use of the smartphones by users make it difficult to detect the motorized intervals accurately (Garg and Singh, 2014). Some drawbacks of published efforts are as follows:

- Use of sensors with high energy consumption or unavailability of continuous sensors (Reddy et al., 2010; Gong et al., 2012)
- Use of heavy processing methods (Hemminki et al., 2013)
- Inability to distinguish between stationary and moving states in motorized mode (Manzoni et al., 2010)
- Low accuracy (Miluzzo et al., 2008; Wang et al., 2010).

Zheng et al. (2010) determined the walking, biking, bus travel, and vehicle travel modes using GPS. The walking mode was detected with 83% accuracy compared with the vehicle mode. High energy consumption of GPS sensors and the inability to

Table 1
Contributions of the smartphone based intelligent transportation systems.

Name	Category	Contribution of the paper	Necessary comments
Aldunate et al. (2013)	Accident detection	They assumed that the smartphones are inside the vehicles without any contribution for finding its location	Accident detection with threshold velocity of 60 km/h to distinguish between motorized and non-motorized modes
White et al. (2011)	Accident detection and traffic monitoring		Usable only for high speed situations
Vaiana et al. (2014)	Driver behavior recognition		
Fazeen et al. (2012)			
Chaovalit et al. (2013)			
Paefgen et al. (2012)			
Chu et al. (2014)			
Eren et al. (2012)			
Eriksson et al. (2008)	Pavement monitoring		
Mednis et al. (2011)			
Bhoraskar et al. (2012)			
Perttunen et al. (2011)			
Astarita et al. (2012)			
Thiagarajan et al. (2010)	User tracking	Walking mode detection	Using high energy consuming GPS sensor and Wi-Fi to detect non-walking states including biking, all stationary states, working with smartphone in stationary states and in vehicle
Reddy et al. (2010)	Mode detection	Motorized mode detection	Detection with 94% accuracy by using high energy consuming sensor GPS
Gong et al. (2012)			Detection with 92% accuracy by using high energy consuming sensor GPS
Zheng et al. (2010)			Detection with 83% accuracy by using high energy consuming sensor GPS
Sohn et al. (2006)			Detection with 85% accuracy, however low accuracy for stationary mode detection (<60%)
Hemminki et al. (2013)			Detection with 85% accuracy, however low accuracy in sensitive application such as accident detection
Wang et al. (2010)			
Manzoni et al. (2010)			Detection with 82% accuracy, however low accuracy in sensitive application such as accident detection
Miluzzo et al. (2008)			Detection with 69% accuracy
Anderson and Muller (2006)			
Yang (2009)			Detection with 66% accuracy using simplified features and somewhat high energy consumption
Wang et al. (2009)			Detection with 74% accuracy
Mohan et al. (2008)	Pavement monitoring and Traffic condition		Using Accelerometer and GSM without any report for motorized mode detection
Hong et al. (2014)	Driver behavior Recognition	They are activated by users	Connection with OBD
Dai et al. (2010)			Manual activation and installation in each trip
Wahlstrom et al. (2015)			
Johnson and Trivedi (2011)			
Castignani et al. (2013)			

detect and analyze stationary states were drawbacks of their research. Gong et al. (2012) used a GPS device and geographical information from ArcGIS to determine the modes based on recorded locations and speeds. The need to send data to a center for analysis was an important limitation of their paper.

The proposed method distinguishes between walking mode and other modes with 92% accuracy. Reddy et al. (2010) estimated vehicle travel modes with 94% accuracy using an accelerometer and GPS. Although this accuracy is acceptable, the method consumed a high amount of energy. In addition, disconnection of GPS in segments such as tunnels made it difficult to cover the results for all situations. Some researchers have used low energy sensors such as GSM or accelerometers. Sohn et al. (2006) used GSM to distinguish 85% of motorized, stationary, and walking modes. Because movement at low velocity in congestion (under 15 km/h) was considered to be a walking mode, the performance of their method was insufficient. This method was also sensitive to the density of BTS antennas and travel behavior.

In contrast to GSM and GPS, the accelerometer can be applied to record gestures and instantaneous accelerations. Thus, it is a good candidate for mode detection. Miluzzo et al. (2008) also used the accelerometer so as to determine the user status such as walking, running, sitting and standing. The modes with 69% accuracy were detected when the smartphone was inside the vehicle. Nevertheless, detection was properly done when the smartphone was outside the vehicle. Manzoni et al. (2010) by means of Fast Fourier Transformation on the obtained wave form of accelerometer data achieved a total of 82% difference between walking and vehicle modes. Nevertheless, the accuracy for the stationary mode was about 70%. Moreover, utilizing the accelerometer by Wang et al. (2010) reveals 79% accuracy in the detection of walking and vehicle modes.

Some features of the accelerometer wave which include skewness, kurtosis, variance and distance between peaks have been considered by Hemminki et al. (2013) to detect various traveling modes. The energy consumption of the proposed technique exploiting 78 different features is 70% greater than the previous research performed by Wang et al. (2010). Their results show that the detection of walking, vehicle movement and stationary modes was about 85%. Some other related work can be found in the study of Adil Mehmood Khan et al. (2014).

In continuation of these studies, in this paper, a new method of using smartphone sensors fusion to detect motorized modes and their stationary states in real-time implementation was proposed. In order to reduce the energy consumption, Inertial Measurement Unit (IMU) sensors including accelerometer, gyroscope and magnetometer were applied. The magnetometer is utilized for pre-processing and filtering noises. The gyroscope is used to determine non-motorized modes, and lastly, the accelerometer is utilized to extract stationary and moving statuses. Extracting modes and statuses are carried out via a rule-based inference engine by extracting the rules from the gyroscope and the accelerometer features and by combining with the human knowledge. The details of this system will be discussed in the later part of the study. Section 2 includes some preliminaries. Section 3 presents the proposed inference engine. Section 4 investigates the energy consumption and Section 5 presents the results with some necessary discussion. The last section ends the paper with a brief conclusion.

2. Preliminaries

Smartphones include a set of sensors like GPS, accelerometer, gyroscope, camera and microphone. Each sensor has capabilities and disadvantages for using it in transportation applications. Nevertheless, the sensors can be chosen to prepare data for ITS application based on the following conditions:

– Convenience application under different circumstances without any limitation to a particular boundary or certain conditions.
– Consuming low energy due to continuous requirement for long-term sampling.
– Adequate accuracy and high sampling rate.

Based on these conditions, the accelerometer, the gyroscope and the magnetometer known as IMU sensors, are good options for ITS applications. In contrast to the sensors like GPS turned on by a user or an application, IMU sensors independent of being used are always activated. In the following, their abilities are given briefly.

Accelerometer: This low energy consuming sensor can be utilized to identify the user activities based on the acceleration records. The high accuracy of this sensor to sense the smallest changes and gestures along the three directions and its high sampling rate makes this sensor applicable for modes determination purposes. Nevertheless, this sensor cannot detect the velocity. It is also important to reorient the device to the vehicle orientation in order to determine the acceleration of the vehicle.

Magnetometer: This sensor measures the magnetic field of the device along three axes. This magnetic field also includes the magnetic field of the earth. So, it can be utilized as a digital compass. Using this ability and its fusion with the gyroscope, it is possible to detect the angle between the device and the coordination axis of the base (Renaudin et al., 2010). This smartphone feature is called the orientation sensor. This sensor also consumes low energy.

Gyroscope: Gyroscope is a sensor that presents angular velocity of rotation along three axes. Its low energy consumption and high accuracy in recording the smallest change directions have made it a good choice for detecting behaviors and maneuvers.

In summarizing the previous research, several researchers utilized the accelerometer for mode detection. Although under ideal conditions, the accelerometer is able to detect the differences between the walking mode and the motorized mode with a high accuracy, the different road conditions, level of congestion, bumps, and driving styles may lead to different changes in the results of this sensor. Furthermore, changing the vehicle, playing with smartphone, continuous stop-movement, and common usage of the smartphone, such as gaming cause other changes similar to the motorized mode. Using gyroscope and magnetometer as well as accelerometer, provides a better occasion to recognize the time intervals of the motorized modes. Fig. 1 depicts the results of an experiment, as well as data collected from IMU sensors of a Galaxy smartphone in one hour. This figure demonstrates that non-motorized transportation mode was better determined by the gyroscope than the accelerometer. On the other hand, the accelerometer is better than the gyroscope in terms of recognizing stationary states. Based on these traces, this study tries to use a fusion of IMU sensors to recognize the transportation modes.

2.1. Modes and statuses

This study attempts to discover situations where the smartphone is located inside the vehicles. These situations include all motorized modes independent of vehicle types such as private cars, motorcycles, buses or subway trains. Moreover, this study identifies the situations where vehicle stops due to various reasons like traffic jam or a red light and detects stationary statuses from moving statuses of the motorized mode. Non-motorized mode can be referred when the device is not located in a motorized vehicle. In this mode, the smartphone may be moved by the user through walking, running, biking, jumping, going up and down the stairs or using elevator and escalator.

The stationary or the moving situation in a mode is also determined via the use of statuses. Thus, stationary status in motorized mode may occur when a vehicle stops in a traffic jam or behind a red light. In addition, moving status in non-motorized mode may occur when the smartphone is moved by the user through walking, running, etc.

Based on these terms, four different mode-status pairs are recognized in this study, these include the following:

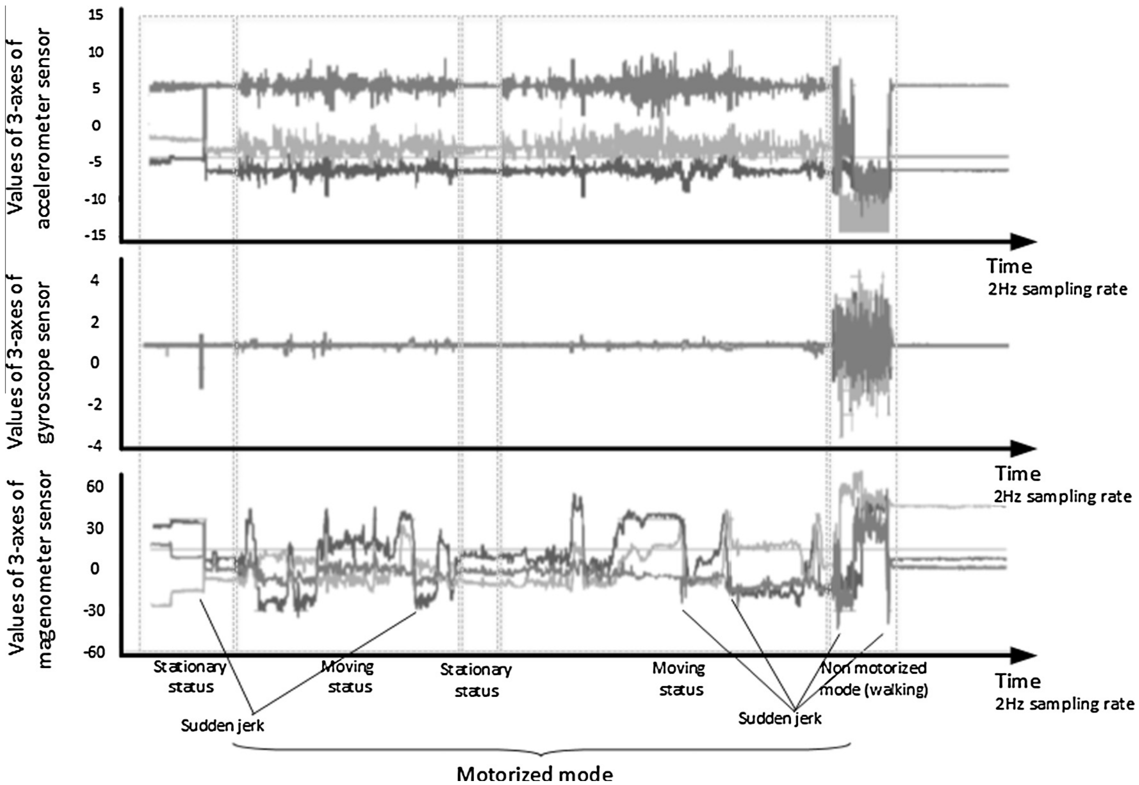

Fig. 1. Motorized vs. non-motorized mode during an hour of IMU data on Samsung Galaxy N8000.

- The moving status in non-motorized mode (MNM).
- The moving status in motorized mode (MM).
- The stationary status in non-motorized mode (SNM).
- The stationary status in motorized mode (SM).

3. The proposed inference engine

3.1. Data acquisition

In the proposed inference engine, IMU sensors data in three axes are recorded continuously. A 2-Hz sampling rate is considered for this study. This sampling rate strongly reduces the computation process and memory space when compared with similar studies. In this study, we define a segment to include 6 samples or covering 3 samples. Two consequence segments overlap in 3 samples (Fig. 2). Determining segment size less than 6 samples, reduces the ability of motorized mode detection, and determining segment size greater than 6 samples increases computation time and complexity.

The motorized or non-motorized segments cover situations where smartphone is inside or outside the vehicle. In addition, the stationary segment can be detected in the motorized or non-motorized situations.

A window includes 40 segments or 120 samples in each axe of each sensor. Each window is assigned to the motorized mode or the non-motorized mode by the proposed engine. Motorized windows alongside stationary segments are stored for future analyses of ITS applications.

3.2. Filtering noises by magnetometer

Sudden jerks and movements of the smartphone, when it is picked up or when it falls from the hands cause intensive shocks to gyroscope and accelerometer sensors. The analysis of the shocks influences the states and modes causing false detections. Different methods are utilized to filter these data, as a costly process, one can refer to Fast Fourier Transformation (FTT) on the accelerometer data (Figo et al., 2010; Hemminki et al., 2013; Manzoni et al., 2010; Wang et al., 2010). But in the proposed engine, a low-cost method is implemented to detect jerks and to remove their influences. Sudden movements and direction changes make quick changes in this sensor during a unit of time, as a result of the measurement of the earth magnetometer. These sudden changes do not take place along with transportation modes. So, samples corresponding to these changes are removed from accelerometer and gyroscope data (Fig. 1).

3.3. Feature extraction

Three features are introduced in the following sub-section, to determine the moving status in the non-motorized mode, the stationary status and the moving status in the motorized mode, applying gyroscope and accelerometer sensors.

3.3.1. Determining the moving status in the non-motorized mode by gyroscope

Although non-motorized mode can be detected through the use of accelerometer and gyroscope, gyroscope is more suitable due to its accuracy when compared to the accelerometer. It should be noted that the moving vehicle in straight line does not affect the angular velocity of the smartphone. On the contrary, the non-motorized movement causes significant angular velocity to the smartphone (Fig 1). In order to reduce the computational cost of reorientation of the smartphone with the direction of vehicle or user movement, L^2-Norm of the three dimensions of gyroscope is taken into consideration. This value is independent of the smartphone direction. Let $g_{x_t}, g_{y_t}, g_{z_t}$ be the angular velocity of smartphone in x, y and z axes in the time sample t, respectively. The new gyroscope feature $G_{\mu s}$ is defined with Eq. (1) as the average of L^2-Norm of gyroscope vectors in 6 samples of segment s:

$$G_{\mu s} = \frac{1}{6}\sum_{t=3s}^{3s+5}\left(\sqrt[2]{g_{x_t}^2 + g_{y_t}^2 + g_{z_t}^2}\right) \tag{1}$$

Fig. 3A shows $G_{\mu s}$ values for the moving status in the motorized and non-motorized modes. The moving status of the non-motorized mode can be determined by applying appropriate threshold θ for $G_{\mu s}$, so we would have:

$$G_{\mu s} > \theta \Rightarrow \boldsymbol{s} \text{ is non-motorized segment} \tag{2}$$

In the next subsection, the method of determining threshold for $G_{\mu s}$ will be described.

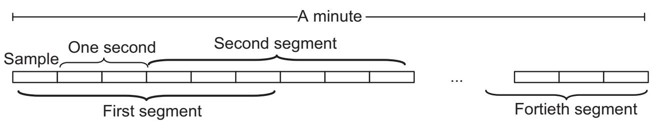

Fig. 2. A segment and a window for analyzing smartphone sensors data.

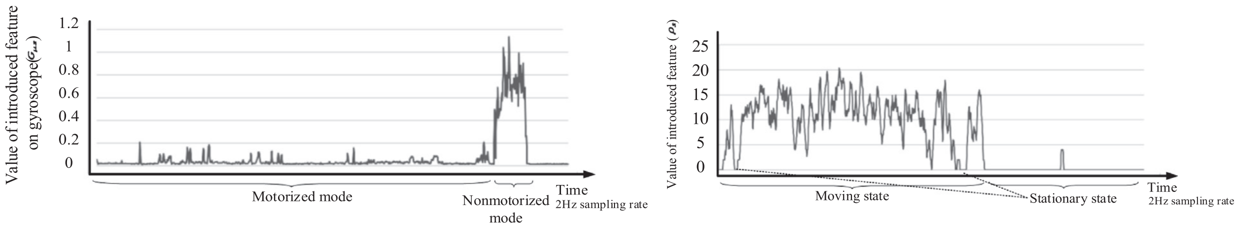

Fig. 3. (A) Values of in the moving status in motorized and non-motorized mode. (B) Values of in moving and stationary status in motorized mode.

3.3.2. Determining stationary status by an accelerometer

Any movement of the smartphone causes swings and changes in accelerometer for either non-motorized or the motorized modes. Thus, the stationary status is expected if significant changes are not recorded by the accelerometer.

Based on this claim to recognize stationary status, if $(a_{x_t}, a_{y_t}, a_{z_t})$ is the acceleration vector in time sample t, the feature $\hat{a}_t$ can be defined as the following L^2-Norm of acceleration vectors:

$$\hat{a}_t = \sqrt{a_{x_t}^2 + a_{y_t}^2 + a_{z_t}^2} \tag{3}$$

The variation of the acceleration changes in the stationary status is less than the acceleration changes in the moving status. Consequently, if ρ_s signifies the variance of the acceleration of the segment s in the next 6 time samples, it can be utilized to identify the stationary status of the motorized or non-motorized mode. Based on this, similar to the previous section, it is simple to define an appropriate threshold such as γ such that:

$$\rho_s < \gamma \Rightarrow \boldsymbol{s} \text{ is stationary segment} \tag{4}$$

Details of finding the threshold are given in the next subsections.

3.3.3. Determining the moving status in the motorized mode

Segments which are neither the stationary status nor the non-motorized mode can be considered as the moving status in the motorized mode. Nevertheless, some user's activities with smartphone such as calling up, gaming, message sending and browsing may satisfy Eqs. (2) and (4). So, the motorized segments must be separated from these segments. Since the effect of the moving state in the motorized mode on the accelerometer and the gyroscope can be sensed simultaneously, the ratio of $G_{\mu s}$ and ρ_s can be considered as follows:

$$\delta_s = \frac{G_{\mu s}}{\rho_s} \quad \text{for each segment } \boldsymbol{s} \tag{5}$$

The moving status of the motorized mode can be determined by applying an appropriate threshold for δ_s. Note that this threshold is applied on the segments similar to the motorized mode. Let λ be the threshold for δ_s, as a result, in each segment such as s, one can check the following:

$$\delta_s < \lambda \text{ and } G_{\mu s}\langle\theta \text{ and } \rho_s\rangle\gamma \Rightarrow \boldsymbol{s} \text{ is the moving segment in the motorized mode} \tag{6}$$

Low processing overhead is one of the key points in these three features $(G_{\mu s}, \rho_s, \delta_s)$, which demonstrates that our approach is more effective when compared with the previous studies where FFT in high sampling rates has been utilized (Hemminki et al., 2013; Wang et al., 2010; Manzoni et al., 2010).

3.4. Determining thresholds

To determine thresholds for the above-mentioned features, optimal thresholding method is utilized based on the minimum error. This method has been applied in image processing to recognize an object region from the background of the

Table 2
Datasets in each feature.

Feature	S1	S2	Universal set
$G_{\mu s}$	{*MNM*}	{*MM*}	{*All moving segments*}
ρ_s	{*SM*}	{*MM*}	{*All motorized segments*}
δ_s	{*MM*}	{*using phone in SNM*}	{*Segments satisfy* $G_{\mu s}\langle\theta$ *and* $\rho_s\rangle\gamma$}

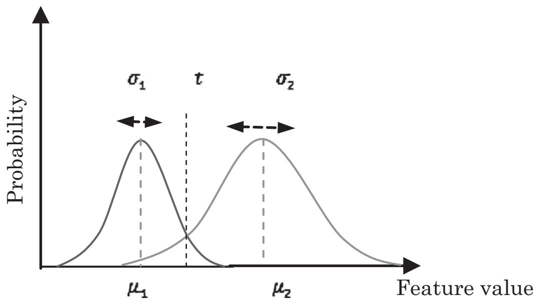

Fig. 4. Determining optimal threshold base on distribution function.

image (Kittler and Illingworth, 1986). There are two regions or two sets of data in each of the proposed feature. Thresholds are utilized to separate these two sets by determining a boundary between them. For instance, the threshold θ for the feature of the moving status in non-motorized mode by gyroscope ($G_{\mu s}$) determines the boundary of *MNM* dataset from *MM*.

Table 2 illustrates the various couples of separated sets $S1$ and $S2$ which are considered in this study. If the distribution function of these sets is determined, as shown in Fig. 4, it is possible to separate them. Since according to the law of total probability, for each sample, one can write:

$$P(x) = \sum_{i=1}^{2} P(x|S_i) \cdot P(S_i) = P(S1) \cdot p_{s1}(x) + P(S2) \cdot p_{s2}(x) \tag{7}$$

where $P(S1)$ and $P(S2)$ are the prior probabilities of $S1$ and $S2$ sets and $p_{s1}(x)$ and $p_{s2}(x)$ are the probabilities of x belonging to $S1$ and $S2$, respectively. If t is considered as a threshold, the probability of error in each set is given by:

$$E_{s1}(t) = \int_{-\infty}^{t} p_{s2}(x)dx, \quad E_{s2}(t) = \int_{t}^{\infty} p_{s1}(x)dx$$

The total probability of false detection that must be minimized is as follows:

$$Min \quad E(x) = P(s2) \cdot E_{s1}(x) + P(s1) \cdot E_{s2}(x) \tag{8}$$

To minimize (8), the following ordinary differential system should be solved:

$$\frac{dE(t)}{dt} = \frac{d(P(S2) \cdot \int_{-\infty}^{t} p_{s2}(x)dx + P(S1) \cdot \int_{t}^{\infty} p_{s1}(x)dx)}{dt} = 0 \tag{9}$$

Based on the first fundamental theorem of calculus, we have:

$$P(S1) \cdot p_{s1}(t) = P(S2) \cdot p_{s2}(t) \tag{10}$$

Thus, after determining distribution functions of datasets and solving (10), the threshold t can be obtained. As a result of unpredictable probability of sets, the same probability can be usually considered for both $P(S1)$ and $P(S2)$.

With this method, it is possible to find the threshold values θ, γ and λ for three features ($G_{\mu s}, \rho_s, \delta_s$) and based on these parameters, the inference engine rules can be implemented to recognize modes and statues. Details of computation are given in the later part of this study.

3.5. Inference engine

Features introduced in the previous subsection are applied in the proposed inference engine given in Fig. 5 where the transitions between the states are defined according to the rules presented in Table 3. In each window, the mode is determined by this inference engine based on the current state and the rules.

In this inference engine, the following situations are considered to define the rules based on the features:

- *Non-motorized mode:* This situation corresponds to the times at which the smartphone device is outside the vehicle and the stationary states are neglected and sensor data are not stored.
- *NtoMTransit:* In this situation, evidence indicates the moving states of the motorized mode. Nevertheless, these pieces of evidence must be verified by the other rules. The state of the smartphone may change to the motorized mode or return to the non-motorized mode, depending on the rules.
- *MtoNTransit:* In this situation, there are some evidences which show that the smartphone owner is outside of the vehicle. But these evidences must be verified by the other rules. Depending on the rules, the state of the smartphone may be changed to the non-motorized mode or returns to the motorized mode.

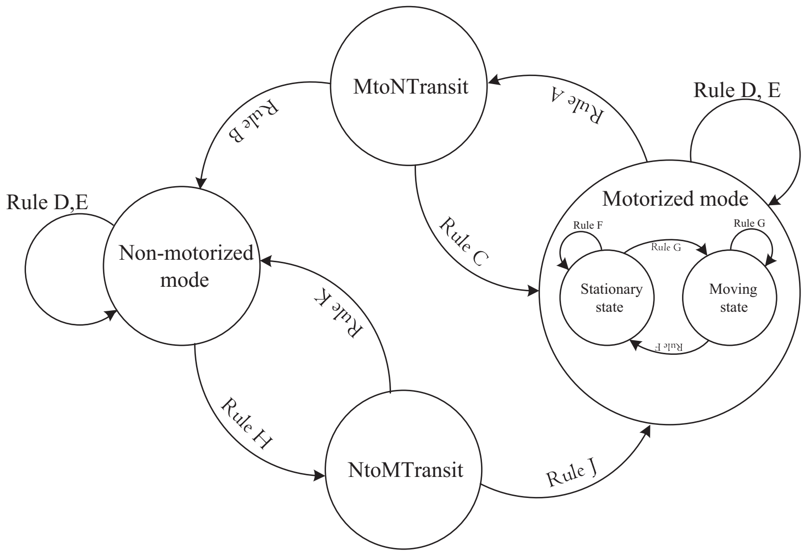

Fig. 5. An inference engine for mode detection based on the rules given in Table 3.

Table 3
Rules for Inference engine Presented in Fig. 5.

Name	Type of rules	Rule description
Rule A	Feature	The observation of $G^+_{\mu s}$ in a segment transfers from Motorized mode to MtoNTrans state
Rule B	Feature	The observation of $G^+_{\mu s}$ in 5 consequent segments transfers from MtoNTrans to Non-motorized mode state
Rule C	Feature	If $G^+_{\mu s}$ is not observed in MtoNTrans state, the state is transferred to Motorized mode
Rule D	Feature	The observation of ρ^-_s in Motorized mode or Non-motorized mode, does not change the state
Rule E	Feature	The observation of ρ^+_s in Motorized mode and the observation of $G^+_{\mu s}$ in Non-motorized mode do not change the state
Rule F	Feature	The observation of ρ^-_s in 2 consequent segments in Motorized mode transfers the state to Stationary state
Rule G	Feature	The observation of ρ^+_s in Motorized mode transfers the state to Moving state
Rule H	Feature	The observation of ρ^+_s and $G^-_{\mu s}$ in Non-motorized mode transfers the state to NtoMTrans state
Rule J	Feature	The observation of δ^-_s in NtoMTrans transfers the state to Motorized mode
Rule K	Feature	The observation of ρ^-_s and $G^+_{\mu s}$ in NtoMTrans transfers the state to Non-Motorized mode
Rule L	Refined	The motorized segments less than 5 s in the Non-motorized mode are not valid
Rule M	Refined	The Non-motorized segments less than 5 s in the Motorized mode are not valid
Rule N	Refined	Segments in 10 s before and after each changing mode is determined similarly based on the most frequently label

Where:
$G^+_{\mu s}$ means $G_{\mu s} > \theta$ and $G^-_{\mu s}$ means $G_{\mu s} \leqslant \theta$.
ρ^+_s means $\rho_s \geqslant \gamma$ and ρ^-_s means $\rho_s < \gamma$.
δ^-_s means $\delta_s < \lambda$

– *Motorized mode:* This situation corresponds to the times at which the smartphone is inside the vehicle. In this state, all data are stored and according to the rules, stationary status is separated from the moving status and their time intervals are sent to ITS applications.

In addition to the rules extracted from features, some refined rules are defined in Table 3, based on human knowledge and expertness. These refining rules increase the accuracy of the motorized mode detection and eliminate noisy segments. Some refining rules may be violated in the theory but in practice, applying these rules does not remove the useful motorized modes.

4. Efficiency of the proposed system

The energy consumption of the smartphone sensors and the applications for N8000 Samsung are illustrated in Table 4. Similar results are presented in other smartphones (Reddy et al., 2010). As can be seen, GPS and Wi-Fi consume more energy than other sensors. This is the main shortcoming of the studies utilizing these sensors (Reddy et al., 2010). In addition, the lack of access to satellites or access points exists. By contrast, IMU sensors consume low amount of energy and because of continuous activeness and availability, the usage of these sensors is value added.

Table 4
Applications and sensor energy consumption in Samsung N8000.

Sensors and applications	Power (mw)
GPS	433
Wi-Fi	1000
LCD light	700
Phone Idle	20
Active Call	780
Video player	900
Bluetooth	230
Accelerometer	2
Magnetometer	10
Gyroscope	4

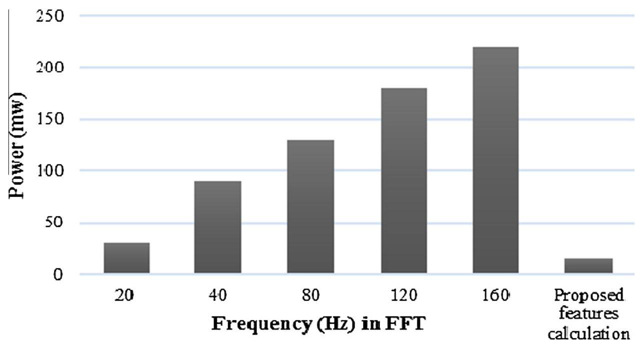

Fig. 6. The CPU energy usage for calculating features.

Table 5
Comparison of energy consumption.

Mode detection system	Energy (mw)
Hemminki et al. (2013)	85
Wang et al. (2010)	50
Reddy et al. (2010)	240
The proposed engine	35

Other issues leading to energy consumption are related to recording and processing of data. In most of the previous studies, Fast Fourier Transformation (FFT) is utilized for calculating features (Thiagarajan et al., 2010). Moreover, studies have shown that the energy consumption in the high rate sampling is 3 times more than that of the low rate sampling (Balan et al., 2014; Yan et al., 2012). Consequently, the high sampling rate increases the CPU usage to calculate features, such as variance and FFT (Yan et al., 2012). Fig. 6 illustrates the CPU energy usage for calculating FFT in different sampling rates versus the energy usage for calculating the features of the proposed engine on a Samsung N8000 smartphone. In a study by Wang et al. (2010), FFT was calculated for 256 samples of the accelerometer wave for every 8 s which consumed 50 MW. Hemminki et al. (2013) also proposed a method with 70% increased energy consumption compared with the latter study, whereas our approach exploits 240 samples every minute and consumes less than 35 MW. Table 5 compares the performance of our proposed engine with the previous mode detection systems. The obtained results reveal that in comparison with the similar methods based on IMU sensors (Wang et al., 2010), the proposed method saves 40% energy and in comparison with GPS-based methods (Reddy et al., 2010), the proposed method saves 600% energy.

5. Accuracy of the proposed system

5.1. Experimental setup

To analyze the strength of the proposed system, 9 different users with different models of smartphones were considered in this study (Table 10). The experiment intends to detect the motorized and non-motorized travel modes. The motorized modes include car, bus, subway, and motorcycle and the non-motorized modes include walking, running, going up and down the stairs and using elevator. The smartphone was located in different places such as in the pocket, in the bag and inside the car seat. During the experiment, the smartphone was randomly used for calling, sending messages, checking emails and

Table 6
Distribution of different travel mode.

Mode	Min	Stationary intervals
Walk	250	–
Run	5	–
Going U/D Stairs	20	–
Car	300	15
Bus	200	85
Subway train	75	30
Motorcycle	45	5

gaming. The experiment includes the different traffic conditions such as congestion, traffic light and stop-movement conditions in the motorized modes. The position and the velocity of the smartphone are also recorded by GPS to compare the results and the time intervals are noted by users. Table 6 presents the distribution of travel modes and status.

5.2. Calculating and validating thresholds and refined rules

To utilize inference engine, in the first step, thresholds must be determined. To determine thresholds, Eq. (10) is applied based on the mean and the standard deviation values of datasets. Based on this, the sensor data obtained from more than 30,000 segments in a period of two days are considered as the training data. Then, for each set, the best fit distribution function is estimated (Appendix A). For instance, segments where the smartphone is being used by the user in the stationary non-motorized mode is referred to as {Using in SNM} set and the segments where the smartphone is located inside a moving vehicle is referred to as {MM} set. The distribution function of values of δ_s in these sets is estimated as lognormal distribution with the mentioned means and standard deviations in Table 7. In Appendix A, distribution functions of six sets (two sets for each three thresholds) are estimated. Table 7 shows the means and the standard deviation for each set and the calculated threshold for each feature by Eq. (10).

To validate thresholds obtained by statistical method, we applied learning machine techniques and compared the accuracy and the precision of results. Based on this, an artificial neural network (NN), KNN, Naïve Bayes (NB) and SVM classifiers in MATLAB 2013b are applied for the binary classification of the data of the experiment given in Table 7. The thresholds obtained from these techniques for the first feature $G_{\mu s}$ and the precision of the classification between the motorized and non-motorized statuses are compared in Table 8. It can be noted that almost similar precision and the accuracy of our statistical approach along with the best results of the machine learning algorithms have occurred and therefore the proposed statistical approach is valid. Note that the experimental thresholds in Table 8 are obtained by smoothly increasing the value of the considered feature until the classes are changed.

To validate the refined rules and to present the results of these rules on the accuracy of the motorized mode detection, the training data are fed to the proposed inference engine. Thereafter, the time intervals which are detected as motorized mode are compared to the ground-truth. Table 9 shows the accuracy of the mode detection based on the application of the refining rules in the training data.

Table 7
Means and standard deviations of datasets and thresholds value.

Features	Datasets	Dist. func.	Parameters	Threshold	Value
$G_{\mu s}$	$\{MNM\}$	Lognormal (3P)	$\sigma = 0.27$ $\mu = 0.77$ $\gamma = -1.14$	θ	0.26
	$\{MM\}$	Gen. Logistic	$k = 0.3$ $\sigma = 0.02$ $\mu = 0.085$		
ρ_s	$\{SM\}$	Lognormal	$\sigma = 1.03$ $\mu = -4.05$	γ	0.09
	$\{MM\}$	Lognormal	$\sigma = 1.156$ $\mu = -0.78$		
δ_s	$\{MM\}$	Lognormal	$\sigma = 1.083$ $\mu = -1.42$	λ	0.85
	{Using in SNM}	Lognormal	$\sigma = 1.40$ $\mu = 1.08$		

Table 8
The accuracy and the precision of different classifiers compare with statistical method.

	Obtained threshold	Precision	Accuracy
SVM	0.86	82	89
NN	0.25	93	95
NB	0.323	92	95
KNN	0.225	94	95
Statistical (our approach)	0.26	93	95

Table 9
The accuracy of motorized mode detection after applying refined rules.

Applying rules	Precision of motorized mode detection (%)
Nothing	93
Rule L	93.7
Rule M, L	96.2
All rules (L, M, N)	97.1

Table 10
Precision and recall for different users.

User	Phone	Motorized vehicle	Mode accuracy (%)	False positive (%)	False negative (%)	Stationary accuracy (%)
User1	Samsung Note	C,M	97.4	4	2.3	99
User2	Samsung Tab	S,B	96.3	3	1.5	98.2
User3	Huawei	S,B	98	2	0	100
User4	Samsung S6	S	92.3	2.6	11	92.5
User5	Samsung Galaxy	S,B	95.5	0.3	9	91.5
User6	Sony	C	96.3	3	1.5	98.2
User7	Samsung Tab	S	92.5	5.3	4	96
User8	Alcatel	C	93.5	0.5	10	100
User9	Nexus	C	95	4	2	98.5
Average results			95.2	2.7	4.6	97.1

B: Bus; C: Car; M: Motorcycle; S: Subway train.

5.3. Results of the proposed engine

To evaluate the performance of the proposed engine, the collected data were divided into one-minute windows and were imported to the inference engine consecutively. Thereafter, the recognized mode and status intervals were stored to be compared with ground truth. Table 10 presents the accuracy of the motorized mode detection for 9 users with different smartphones and their stationary statuses in each smartphone.

The false positive demonstrates the percentage of intervals detected as the motorized mode but smartphone in these intervals was not located inside the vehicle. The false negative represents the percentage of intervals where the smartphone is located inside the vehicle, but the proposed engine cannot detect these intervals as the motorized mode. Results presented in Table 10 demonstrate that the average of the accuracies of the proposed inference engine is greater than 95.2% for the motorized detection. In detecting stationary status in the motorized mode, the average of the accuracies is 97.1%. These results confirm the capability of the proposed inference engine.

Fig. 7A illustrates the results of the motorized intervals detected by the proposed inference engine compared with ground truth during a day. According to these results, false detection has occurred in the first segments of the changing mode. Because of transit states including *MtoNTrans* and *NtoMTrans*, the inference engine preserves the previous mode. So in some cases with few lags, the inference engine needs sufficient evidence to detect the changing mode. This delay is normally less than 2 min.

To compare the results of the proposed inference engine with the learning machine techniques, we utilized Neural Network (NN), Naïve Bayes (NB) and Decision Tree (DT) in MATLAB 2013b, and evaluated their results for mode detection by considering the ground-truth data. Table 11 presents the precision of these methods when compared with the proposed inference engine. It is obvious that the performance of the proposed inference engine is essentially better than the applied machine learning algorithms.

In addition, Fig. 7B illustrates the results of motorized intervals detected by ANN compared with ground truth during the course of one day. By comparing this figure with Fig. 7A, one can understand that the false detection of the proposed

Table 11
Comparison between the precision of motorized mode detection by learning machine techniques vs. the proposed inference engine.

Techniques	Precision (%)
NB	85
DT	90
NN	89
Inference engine	95.2

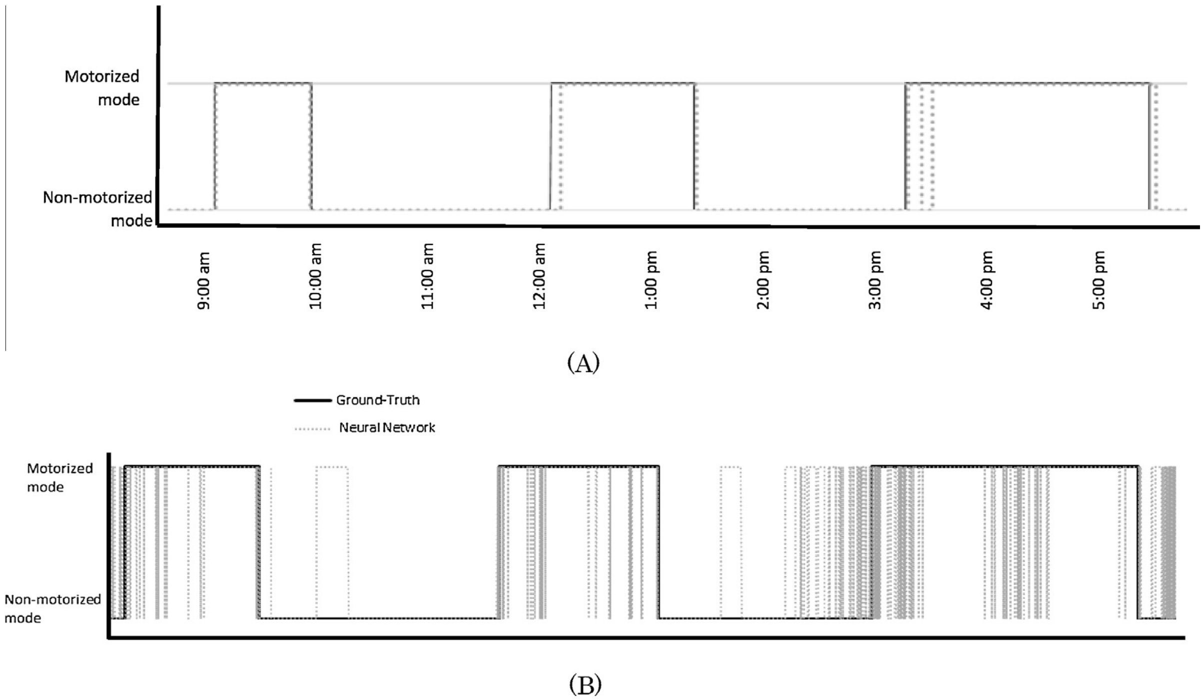

Fig. 7. The comparison between the detected mode by inference engine and ground-truth (a) and between neural network and ground-truth (B).

inference engine is strictly less than the same results of the ANN algorithm which proves the performance of the proposed inference engine.

5.4. Discussion

To compare the performance of the proposed inference engine with the related studies, two issues must be taken into consideration:

First; this study does not focus on the detection of motorized types such as car, bus or subway. Using this model, sensors data of smartphone are effectively prepared for ITS applications, including detection of the motorized type or recognition of the congestion. In some related research (Sohn et al., 2006; Reddy et al., 2010), three modes (motorized, non-motorized and stationary) have been investigated and in other cases different types of motorized mode have been recognized. In latter cases, the accuracy of all motorized modes is considered for comparison with the proposed inference engine in this study. Also, in all related studies, the stationary statuses were assumed to be in some time intervals where the smartphone does not

Table 12
The accuracy of mode detection in different systems.

Methods	Used Sensor(s)	Accuracy of detection	
		Motorize mode	Stationary mode
Reddy et al. (2010)	GPS, Accelerometer	94	95.6
Gong et al. (2012)	GPS,GIS	92	92
Zheng et al. (2010)	GPS	83	85
Sohn et al. (2006)	GSM	85	60
Hemminki et al. (2013)	Accelerometer	85	80
Wang et al. (2010)	Accelerometer	79	90
Manzoni et al. (2010)	Accelerometer	82	70
Milluzzo et al. (2008)	Accelerometer	69	50
Android API[b]	Accelerometer[a]	81	–
Android API[c]	Accelerometer[a]	70	–
The proposed approach	Accelerometer, gyroscope, magnetometer	95.2	97.1

[a] Another used sensor are not mentioned.
[b] confidence value more than 50.
[c] confidence value more than 75 (Google, 2016).

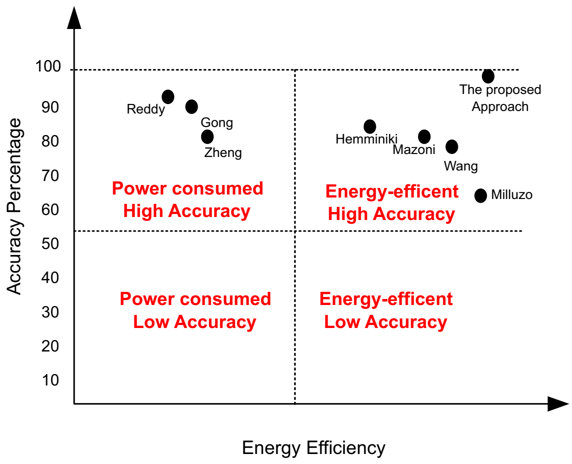

Fig. 8. The comparison of approaches in energy-accuracy perspective.

move. But in our proposed engine, the stationary status is referred to the situations where the smartphone is located inside a stopped vehicle, and this recognition is more difficult than the previous detection, due to the impact of vehicle engine on the smartphone sensors especially on the accelerometer. Table 12 shows the accuracy of the motorized mode and stationary status detection for the previous research and the results of the proposed inference engine. It can be noted that the results of the proposed inference engine for mode detection and stationary detection is certainly better than the previous studies.

Secondly; because of the limitation of the smartphone batteries, memory usage and also processing hardware, the energy consumption, the amount of saved data and the processing needs of models are very important concepts. Although the memory usage in the proposed inference engine is less than that in other studies, due to the ignoring of unused interval times and appropriate sampling rate, the memory usage of the mode detection algorithms is not significant and can be neglected compared with other smartphone applications. In contrast, energy consumption for sensors and processing power for running algorithms still remain as the two significant challenges facing ITS applications. As presented in Fig. 8, neither the usage of battery drained sensors such as GPS nor the usage of inexact procedure causes the proposed inference engine to provide a good opportunity to detect modes with a reasonable accuracy compared to previous studies.

6. Conclusion

Using smartphone is one of the most cost effective approaches to collect and to process information in different contexts of ITS applications. This device includes variant sensors such as accelerometer, gyroscope, magnetometer and GPS which can be utilized for accident detection, evaluation of driver behavior, traffic monitoring, and road pavement management. But usable and relevant information for ITS applications should be acquired from the large amount of data collected by this device.

In this study, a new inference engine was proposed to detect time intervals at which the smartphone is inside the vehicle together with stationary status when the vehicle stops due to various reasons like traffic jam or red light. To detect these intervals, in the first step, the outlying and noisy data are filtered by the magnetometer. Thereafter, motorized modes and their status are detected via an inference engine. Changing state in this inference engine is based on two categories of rules. The first sets of rules are extracted based on the features of gyroscope and accelerometer. The second ones are defined based on the human knowledge to increase the accuracy of detection and to remove false positives.

The proposed method detects 95.2% of the time intervals at which the smartphone is inside the vehicle, although the best result was reported by Reddy et al. (2010) with 94% accuracy by consuming high energy sensors, while our system saves energy as well. Moreover, the proposed engine determines the stationary status in the motorized mode with at least an overall accuracy of 97.1% which is better than the previous studies.

Note that the proposed engine for mode detection is dependent on IMU sensors which are always active and accessible. In comparison with Wi-Fi and GPS, IMU sensors consume low energy. Moreover, the proposed method applies low power features to develop an inference engine. In comparison with the similar methods based on IMU sensors, the proposed method saves 40% energy and in comparison with the methods based on GPS sensors, the proposed method saves 600% energy.

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Appendix A. Estimation distribution function for datasets

Feature	Datasets	Dist. func.	Parameters	Statistical test (Kolmogorov–Smirnov)			
				Statistic	α	Critical value	Result
$G_{\mu s}$	$\{MNM\}$	Lognormal (3P)	$\sigma = 0.27$ $\mu = 0.77$ $\gamma = -1.14$	0.04644	0.05	0.06634	Pass
	$\{MM\}$	Gen. Logistic	$k = 0.3$ $\sigma = 0.02$ $\mu = 0.085$	0.01626	0.05	0.04292	Pass
ρ_s	$\{S\}$	Lognormal	$\sigma = 1.03$ $\mu = -4.05$	0.04851	0.05	0.07091	Pass
	$\{MM\}$	Lognormal	$\sigma = 1.156$ $\mu = -0.78$	0.02714	0.05	0.05436	Pass
δ_s	$\{MM\}$	Lognormal	$\sigma = 1.083$ $\mu = -1.42$	0.0604	0.05	0.08	Pass
	{Using in SNM}	Lognormal	$\sigma = 1.40$ $\mu = 1.08$	0.0588	0.05	0.101	Pass

$$Lognormal(3P) = \frac{\exp\left(-\frac{1}{2}(\ln(x-\gamma)-\mu)^2\right)}{(x-\gamma)\sigma\sqrt{2\pi}} \quad Three\ parameter(\sigma, \mu, \gamma)$$

$$Lognormal = \frac{\exp\left(-\frac{1}{2}(\ln(x)-\mu)^2\right)}{(x)\sigma\sqrt{2\pi}}$$

$$Generalized\ logistic = \frac{\left(1+k\left(\frac{x-\mu}{\sigma}\right)\right)^{\frac{-1-k}{k}}}{\sigma\left(1+\left(1+k\left(\frac{x-\mu}{\sigma}\right)\right)^{-\frac{1}{k}}\right)^2}, \quad 1+k\left(\frac{x-\mu}{\sigma}\right) > 0$$

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