Classification of Vehicles using Magnetic Field Angle Model

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ISMS 2013, Bangkok, Thailand

29th January 2013

Funded by DIT-ASTEC Wireless Sensor Project, Department of Information Technology, Ministry of Communications & Information Technology, Govt. of India.

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    2. traffic flow speed
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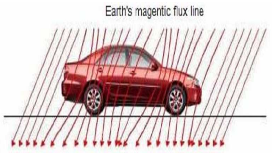
- Induction loop and Video-Image are used most widely technologies but they have a lot of disadvantages.
    1. Induction loops are big in size with difficulty in maintenance.
    2. Video-Image based sensor are costly with big influence of external light conditions.

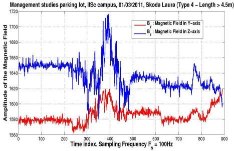
Classification of Vehicles Using Magnetic Signatures

- Passive magnetometers[1] that are capable of sensing the magnetic field can be used. The motes having these sensors mounted on them can be programmed with a vehicle detection algorithm[2].
- High level of flexibility in their deployment configuration and costs less.



a. magnetic perturbations

b. AMR sensor



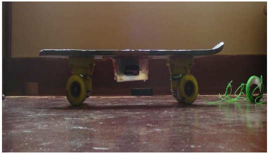
c. sensor readings

[1] Anisotropic Magnetoresistive(AMR) sensors detect the distortions of the earth's magnetic field, which is assumed to be uniform over a wide area on the scale of kilometers.

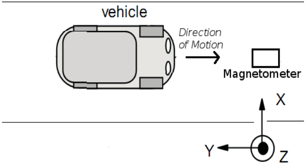
[2] S.Y. Cheung and P. Varaiya, Traffic surveillance by wireless sensor networks, research note, University of California, Berkeley,Jan 2007. http://www.its.berkeley.edu/publications/UCB/2007/PRR/ UCB-ITS-PRR-2007-4.pdf.

- Data is collected using two different mechanism.

(a) Remote Controlled Car



(b) Skate Board



Paths across which the HMC1502 sensor mounted on a TelosB wireless mote placed in a fiber casing, with either a remote control car setup or skate board setup, was moved.

Database - Vehicle Magnetic Signatures

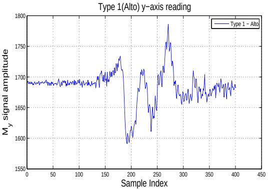
Vehicle Magnetic Signature Database[3] grouped based on the length of the car

Car-type	Type 1	Type 2	Type 3	Type 4
Car Length (in *meters*)	(3.0-3.5)	(3.5-4.0)	(4.0-4.5)	(>4.5)
Type of *Car(n), where n represents number of datasets Cars = 42 Sets = 89	[1]800(8) [1]Alto(2) [2]Matiz(3) [3]Santro(5) [1]Omni(6) [9]Spark(1) [4]Nano(2) [1]WagonR(4) [1]Estillo(3) [9]Beat(2) [13]Reva(1)	[11]Corsa(2) [3]i20(1) [5]Figo(2) [3]GetZ(2) [3]i10(4) [4]Indica(6) [7]Palio(1) [1]Swift(2) [1]Zen(2) [3]Ritz(1)	[3]Accent(1) [2]Cielo(1) [6]City(4) [12]Vento(1) [1]SX4(2) [3]Verna(1) [1]Esteem(2) [4]Indigo(2) [1]Dzire(1) [4]Sumo(1) [5]Fiesta(1) [6]Petra(1) [14]Logan(1)	[6]Civic(1) [8]Corolla(1) [3]Elentra(2) [8]Innova(2) [7]Linea(1) [3]Sonata(1) [10]Octiva(1) [10]Laura(1)
Number of Datasets	87	67	53	27

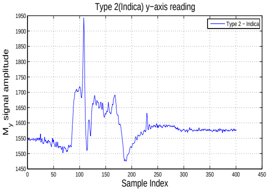
* Indicates the Car Manufacturer

1 - Maruti Suzuki; 2 - Daewoo; 3 - Hyundai; 4 - Tata Motors; 5 - Ford; 6 - Honda; 7 - Fiat; 8 - Toyota; 9 - Chevrolet; 10 - Skoda; 11 - Opel; 12 - Volkswagon; 13 - Mahindra; 14 - Renault.

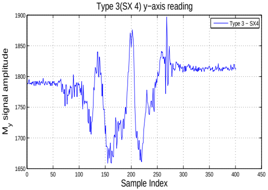
[3] A. S. Bhat, A. K. Deshpande, K. G. Deshpande, and K.V.S. Hari, "Vehicle detection and classification using magnetometer - data acquisition," tech. rep., 2011.



(e) Y-axis reading for Type 1 - Maruti Alto



(f) Y-axis reading for Type 2 - Tata Indica



(g) Y-axis reading for Type 3 - Maruti SX4

(h) Y-axis reading for Type 4 - Hyundai Sonata

The Y-axis trajectories obtained using HMC1502 magnetometer of cars belonging to different types (Length of Car(in$m$) - (3.0-3.5) $\in$ Type 1; (3.5-4.0) $\in$ Type 2; (4.0-4.5) $\in$ Type 3; ($>$4.5) $\in$ Type 4) are shown.

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1. Data Modeling of magnetic signature
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3. Use classification techniques and study the performance of the classifier.

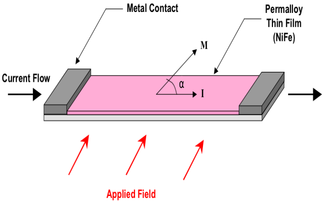


Figure: AMR Element with Applied Field H parallel to the surface of the permalloy. The direction of the current is perpendicular to the applied field. The magnetization vector makes an angle α with the current vector

- The resistance of an AMR sensors is given by:

$$R = \begin{cases} R_0 + \Delta R_0 \left(1 - \dfrac{H^2}{{H_0}^2}\right), & \sin^2\alpha = \dfrac{H^2}{{H_0}^2} \quad \text{for } H \leq H_0 \\ R_0, & \sin^2\alpha = 1 \quad \text{for } H > H_0 \end{cases} \tag{1}$$

- The magnetoresistive effect can be linearized by depositing aluminum stripes (barber poles), on top of the permalloy strip at an angle of 45° to the strip axis. For sensors using barber poles arranged at an angle of ±45° to the strip axis, the following expression for the sensor characteristic can be derived:

$$R = R_0 + \frac{\Delta R_0}{2} \pm \Delta R_0 \left(\frac{H}{H_0}\right)\sqrt{1 - \frac{H^2}{{H_0}^2}} \tag{2}$$

Determining Rotation Angle α

- If all four resistor values R_1, R_2, R_3 and R_4, the supply voltage V_s are known and the resistance of the galvanometer is high enough such that I_g is negligible, then the voltage across the bridge V_G can be found by working out the voltage from each potential divider as follows:

$$V_{BD} = V_G = \left(\frac{R_4}{R_3 + R_4} - \frac{R_2}{R_2 + R_1} \right) V_s. \tag{3}$$

- The resistances of a Wheatstone bridge are such that, resistances R_1 and R_4 increase, and resistances R_2 and R_3 decrease, due to the alignment of barber poles, when an external magnetic field is applied.

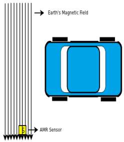
$$R_1 = R_4 = R_0 + \frac{\Delta R_0}{2} + \Delta R_0 \left(\frac{H}{H_0} \right) \sqrt{1 - \frac{H^2}{{H_0}^2}} \tag{4}$$

$$R_2 = R_3 = R_0 + \frac{\Delta R_0}{2} - \Delta R_0 \left(\frac{H}{H_0} \right) \sqrt{1 - \frac{H^2}{{H_0}^2}}. \tag{5}$$

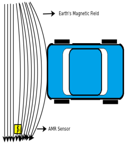
- Substituting and multiplying with the Op-Amp gain constant G we get,

$$V_{BD} = G \left(\frac{K}{1 + K} \right) (\sin 2\alpha) V_s. \tag{6}$$

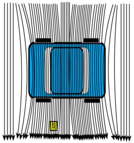
$$\implies \alpha = \frac{1}{2} \sin^{-1} \left(\frac{V_{BD}}{V_s} \left(1 + \frac{1}{K} \right) \frac{1}{G} \right). \tag{7}$$



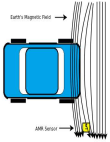
(a) Unperturbed Earth's magnetic field



(b) The flux lines bend towards the vehicle approaching



(c) Flux density increases as the vehicle is right above the sensor



(d) The flux lines bend away as the vehicle crosses the sensor

Observations

1. A change in the number of magnetic flux lines is equivalent to change in the induced magnetic field.
2. This in-turn changes the angle between the internal magnetization vector and the direction of current of the anisotropic mangetoresistances, which makes the bridge unbalanced.

1. Let g be a non-linear function with input α_k, where α_k is the angle between the internal magnetization vector and direction of current at kT_s time-instant.
2. Let y_k be the measured output and η_k be the measurement noise at kT_s time-instant. In the signal processing framework, the sensor model can be defined as follows.

$$\begin{aligned} y_k &= g(\alpha_k) + \eta_k \\ &= G\left(\frac{K}{K+1}\right)\sin(2\alpha_k)V_s + \eta_k. \end{aligned} \tag{8}$$

3. In order to reduce sensor model error and the complexity of computing α at every time-instant, we assume α is constant over a segment of length L.
4. Let $\alpha(j)$ represents the rotation angle value in the j^{th} segment. With this assumption, we estimate the segmented α values based on Least Squares (LS) cost function.

$$\begin{aligned} \hat{\alpha}(j) &= \arg\min_{\alpha(j)} \sum_{i=1}^{L} \left| y_{(j-1)L+i} - g(\alpha(j)) \right|^2, \\ &\quad \text{subject to } |\alpha(j)| \leq \frac{\pi}{4}, \text{where } j \in \{1, \cdots, \lfloor N/L \rfloor\}. \end{aligned} \tag{9}$$

SMFA Algorithm

Segmented Magnetic Field Angle Algorithm (SMFA Algorithm)

Input: Smoothed Vehicle Magnetic Signature - $a_{N\times 1}$

1: Subtract every $k^{th}, k \in \{1, \dots, N\}$ sample with the mean of first $N/10$ samples of $a_{N\times 1}$

2: **for** j=1 to $\lfloor N/L \rfloor$ **do**

3: Estimate $\hat{\alpha}(j)$

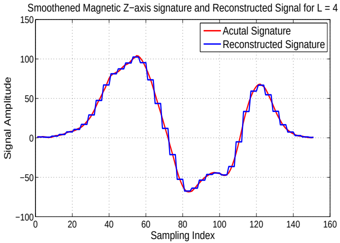
$$\hat{\alpha}(j) = \arg\min_{\alpha(j)} \sum_{i=1}^{L} \left| a_{(j-1)L+i} - g(\alpha(j)) \right|^2$$

subject to $|\hat{\alpha}(j)| \leq \frac{\pi}{4}$

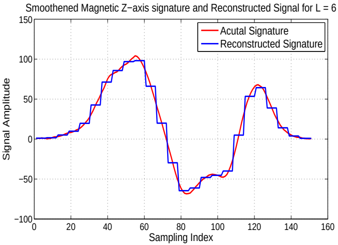
4: **end for**

Output: α_{min} = minimum of $\hat{\boldsymbol{\alpha}}$, α_{max} = maximum of $\hat{\boldsymbol{\alpha}}$, Q = no. of non-zero bins of $\hat{\boldsymbol{\alpha}}$ histogram for bin-size W.

Simulation Results



(e) Curve Fit for a Tata Indica Car for $L = 4$



(f) Curve Fit for a Tata Indica Car for $L = 6$

Table: Features Extraction using SMFA Algorithm for a Tata Indica Car's Magnetic Signature

Seg. Len	α_{min}	α_{max}	Q for $W =$			$RMSE$
			1°	2.5°	5°	
$L = 4$	-15.49°	$+25.75^\circ$	20	11	6	4.78
$L = 6$	-14.76°	$+24.28^\circ$	17	10	5	7.30

- The computational complexity of the LS cost function is of the order $O(\lfloor N/L \rfloor)$. As the value of L increases, the $\overline{RMSE}$ value increases. But, this does not help us in choosing a value of L on which the classification algorithm can be performed.

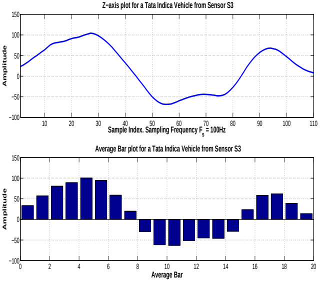
Table: Computational Complexity and $\overline{RMSE}$ Across Available Datasets

Segment Length	Order of Complexity	$\overline{RMSE}$[4]
$L = 4$	$O(\lfloor N/4 \rfloor)$	3.381
$L = 6$	$O(\lfloor N/6 \rfloor)$	4.689

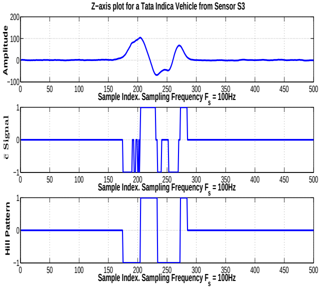
[4] In order to check the variation of $RMSE$ as the number of dipoles M increases, we calculate the average $RMSE$ for all the datasets 'D' across different values of M.

$$\overline{RMSE} = \frac{1}{D} \sum_{i=1}^{D} RMSE_i \qquad (10)$$

Existing Algorithms[5] for Feature Extraction



(g) Average-Bar Transform: Here the vehicle signature vector of length N, is divided into S sub-vectors. The mean value of each sub-vector is calculated and the obtained values for S sub-vector is the feature vector. The value of S is fixed for all classes of vehicles.



(h) Hill-Pattern Transform: This method transforms the signal into a sequence of $\{+1, -1\}$ and without losing much information. This extracts the pattern of "peaks" and "valleys" (local maxima and minima) of the input signal. The sequence of $\{+1, -1\}$ is used as a feature vector.

[5] S.Y. Cheung and P. Varaiya, Traffic surveillance by wireless sensor networks, research note, University of California, Berkeley,Jan 2007. http://www.its.berkeley.edu/publications/UCB/2007/PRR/ UCB-ITS-PRR-2007-4.pdf.

- A vehicle can be modeled as an array of dipoles.

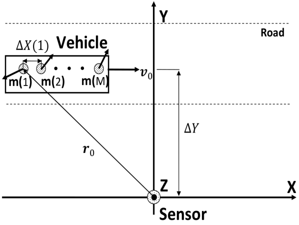


Illustration of a Magnetic Dipole Model for a Vehicle. $\mathbf{m}(i)$ where, $i \in \{1, \ldots, M\}$ represents magnetic dipole moments, $\Delta X(j)$ where, $j \in \{1, \ldots, M-1\}$ is the separation between adjacent dipoles, ΔY and ΔZ are the offsets, $\mathbf{v}_0$ be the velocity of the vehicle and $\mathbf{r}_0$ be distance of $\mathbf{m}(1)$ from the sensor placed at the origin.

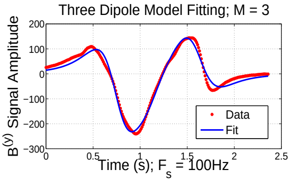


Figure: 3-Dipole Model curve fit for a Tata Indica magnetic reading.

m-Dipole Model with Dipole Separation, Dipole Moments and RMSE for a Tata Indica Car's Magnetic Signature

M-Dipole	$\Delta X(j)$	$\tilde{\mathbf{m}}(i) = \frac{\mathbf{m}(i)}{\|\mathbf{m}(i)\|_2}$
3-Dipole	0.474 0.370	$\tilde{\mathbf{m}}(1) = (-0.77, +0.33, -0.52)$ $\tilde{\mathbf{m}}(2) = (+0.26, -0.18, +0.94)$ $\tilde{\mathbf{m}}(3) = (-0.71, -0.19, -0.67)$

[6] Prateek, G V; Rajkumar, V; Nijil, K; K.V.S. Hari; , "Classification of vehicles using magnetic dipole model," TENCON 2012 - 2012 IEEE Region 10 Conference , vol., no., pp.1-6, 19-22 Nov. 2012 doi: 10.1109/TENCON.2012.6412314

Classification Metric

- We assume L_{tr} and L_{ts} to be the number of training and testing datasets picked. We define the correct rate of classification, C_R as follows

$$C_R = \frac{1}{I} \sum_{i=1}^{I} \frac{\Omega_i}{L_{ts}} \tag{11}$$

where Ω_i is the number of vehicles classified correctly among L_{ts} number of cars in the i^{th} iteration and the total number of iterations is I.

Classification Using SVM

- The goal of a Support Vector Machine(SVM) is to produce a model (based on the training data) which predicts the target value of the test data given only the test data attributes.
- Table shows the C_R value for different segment lengths, $L \in \{4, 6\}$, across different bin-size W for Type 1 (length of the car lies between $3.0m$ to $3.5m$) vs Type 4 (length of the car lies between $4.5m$ to $5.0m$). The value of $I = 100$ is fixed in all our simulations and based on the C_R values obtained, the SVM performs the best for segment length of $L = 6$.

Table: Percentage of Correct Rate of Classification C_R for Type 1 vs Type 4 Cars Based on SMFA Algorithm

Dataset Length	Segment	Bin Size		
(L_{tr}, L_{ts})	Length	1.0°	2.5°	5.0°
(70,44)	$L = 4$	77.92	77.16	77.67
	$L = 6$	78.23	77.23	77.88
(80,34)	$L = 4$	76.33	76.39	76.55
	$L = 6$	77.00	77.03	77.76
(90,24)	$L = 4$	79.17	78.87	79.09
	$L = 6$	79.65	79.57	**80.48**

Classification Using SVM

Table: Percentage of Correct Rate of Classification C_R for Type 1 vs Type 4 Car for Average Bar, Hill Transform, MDMS Algorithm and SFMA Algorithm

Datasets	Feature Extraction Algorithms						
(L_{tr} , L_{ts})	Average Bar Algorithm	Hill Transform Algorithm	MDMS Algorithm		SMFA Algorithm		
			3-DM Normalized Moments $\tilde{\mathbf{m}}$	3-DM Dipole Separation ΔX	Segment Length $L = 6$		
					$W = 1^{\circ}$	$W = 2.5^{\circ}$	$W = 5^{\circ}$
(70,44)	72.70	76.33	73.80	74.14	77.23	77.23	77.88
(75,39)	73.42	75.32	72.70	73.29	77.37	77.37	77.66
(80,34)	73.88	75.39	74.12	74.27	77.00	77.03	77.76
(85,29)	75.36	78.43	76.40	76.61	79.61	80.25	79.89
(90,24)	76.26	77.91	76.67	76.78	79.65	79.57	**80.48**

Table: Percentage of Correct Rate of Classification C_R for Type 1 & Type 2 vs Type 3 & Type 4 Car for Average Bar, Hill Transform, MDMS Algorithm and SFMA Algorithm

Datasets	Feature Extraction Algorithms						
(L_{tr} , L_{ts})	Average Bar Algorithm	Hill Transform Algorithm	MDMS Algorithm		SMFA Algorithm		
			3-DM Normalized Moments $\tilde{\mathbf{m}}$	3-DM Dipole Separation ΔX	Segment Length $L = 6$		
					$W = 1^{\circ}$	$W = 2.5^{\circ}$	$W = 5^{\circ}$
(110,124)	61.74	63.88	63.25	63.55	67.28	67.56	67.47
(120,114)	62.79	64.27	63.97	64.16	67.94	67.89	67.90
(130,104)	63.28	64.73	63.32	63.71	68.04	67.57	68.31
(140,94)	62.80	64.42	63.30	63.61	67.85	67.18	68.04
(150,84)	63.00	64.37	63.95	64.31	68.27	68.23	**68.67**

Thank you