Classification of Vehicles Using Magnetic Dipole Model

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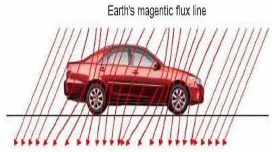
Motivation for Classification of Vehicles

- One important requirement for a traffic management system is the capability to detect the presence of a vehicle and type of a vehicle (car, bus, truck, etc). Based on such detection, statistics such as
  - vehicle count
  - traffic flow speed
  - occupancy
- Induction loop and Video-Image are used most widely technologies but they have a lot of disadvantages.
  - Induction loops are big in size with difficulty in maintenance.
  - Video-Image based sensor are costly with big influence of external light conditions.

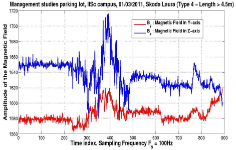
Classification of Vehicles Using Magnetic Signatures

- Passive magnetometers* 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†
- High level of flexibility in their deployment configuration and costs less.



a. magnetic perturbations

b. AMR sensor



c. sensor readings

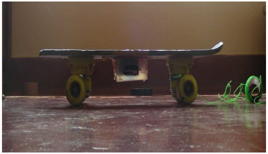
* Anisotropic Magnetoresistive(AMR) sensors detect the distortions of the earth's magnetic field, which is assumed to be uniform over a wide area on the scale of kilometers.

† 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.

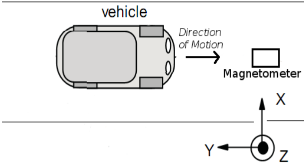
Data Collection

- 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‡ grouped based on the length of the car

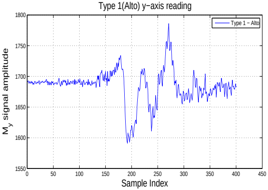
Car-type	Type 1	Type 2	Type 3	Type 4
Car Length (in *meters*)	(3.0-3.5)	(3.5-4.0)	(4.0-4.5)	(>4.5)
Type of *Car(n), where n represents number of datasets Cars = 42 Sets = 89	[1]800(8) [1]Alto(2) [2]Matiz(3) [3]Santro(5) [1]Omni(6) [9]Spark(1) [4]Nano(2) [1]WagonR(4) [1]Estillo(3) [9]Beat(2) [13]Reva(1)	[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

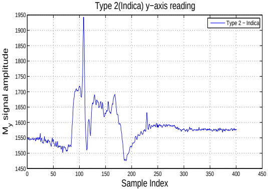
[1] - Maruti Suzuki; [2] - Daewoo; [3] - Hyundai; [4] - Tata Motors; [5] - Ford; [6] - Honda; [7] - Fiat; [8] - Toyota; [9] - Chevrolet; [10] - Skoda; [11] - Opel; [12] - Volkswagon; [13] - Mahindra; [14] - Renault.

‡ 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.

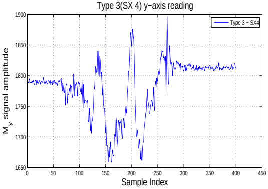
Sample Magnetic Signatures



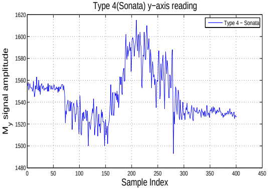
(e) Y-axis reading for Type 1 - Maruti Alto



(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.

Problem Statement:

"To classify vehicles using magnetic signatures obtained from passive magnetometers."

Steps involved in solving

- Data Modeling of magnetic signature
- Extraction of feature vector from the magnetic signature.
- Use classification techniques and study the performance of the classifier.

DATA MODEL - MAGNETIC DIPOLE MODEL§

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

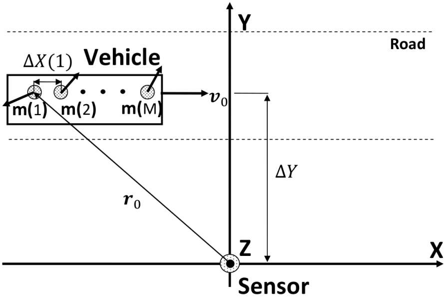


Illustration of a Magnetic Dipole Model for a Vehicle. $\mathbf{m}(i)$ where, $i \in \{1, \ldots, M\}$ represents magnetic dipole moments, $\Delta X(j)$ where, $j \in \{1, \ldots, M-1\}$ is the separation between adjacent dipoles, ΔY and ΔZ are the offsets, $\mathbf{v}_0$ be the velocity of the vehicle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

§ N. Wahlstrom, J. Callmer, and F. Gustafsson, "Magnetometers for tracking metallic targets," in *Information Fusion (FUSION), 2010*

DATA MODEL - MAGNETIC DIPOLE MODEL[¶]

- If the distance from the object is large in comparison with its characteristic length, the induced magnetic field $\vec{B}(\mathbf{r},\mathbf{m})$ at position $\mathbf{r} = [x, y, z]^T$ relative to the object can be described as a magnetic dipole field is given as

$$\vec{B}(\mathbf{r},\mathbf{m}) = \frac{\mu_0}{4\pi}\frac{3(\mathbf{r}\cdot\mathbf{m})\mathbf{r} - r^2\mathbf{m}}{r^5} \tag{1}$$

  where $\vec{B}(\mathbf{r},\mathbf{m}) = [B^{(x)}(\mathbf{r},\mathbf{m}), B^{(y)}(\mathbf{r},\mathbf{m}), B^{(z)}(\mathbf{r},\mathbf{m})]^T$, $\mathbf{m} = [m^{(x)}, m^{(y)}, m^{(z)}]^T$ is the magnetic dipole moment, $r = \|\mathbf{r}\|_2$ is the L^2-Norm and $(\mathbf{r}\cdot\mathbf{m})$ is the scalar dot product of the two vectors.

- Substituting $\mathbf{r} = [x, y, z]^T$ and $\mathbf{m} = [m^{(x)}, m^{(y)}, m^{(z)}]^T$ in equation (1) gives the following

$$B^{(x)}(\mathbf{r},\mathbf{m}) = \frac{\mu_0}{4\pi}\frac{(3x^2 - r^2)m^{(x)} + 3xym^{(y)} + 3xzm^{(z)}}{r^5} \tag{2}$$

[¶] N. Wahlstrom, J. Callmer, and F. Gustafsson, “Magnetometers for tracking metallic targets,” in *Information Fusion (FUSION), 2010*

Sensor Independent Approach

- In the signal processing framework, a sensor can be modeled as a time-invariant system

$$\mathbf{y}_k = f(\mathbf{r}_k, \mathbf{m}_k) + \mathbf{e}_k \quad (3)$$

$$= \frac{\mu_0}{4\pi} \frac{3(\mathbf{r}_k \cdot \mathbf{m}_k)\mathbf{r}_k - r_k^2 \mathbf{m}_k}{r_k^5} + \mathbf{e}_k \quad (4)$$

- The number of parameters to be estimated for an M-dipole model is $4M + 1$

$$\mathbf{p} = [\mathbf{m}(i)^T, \Delta X(j), \Delta Y, \Delta Z]^T$$

- The vehicle is assumed to move parallel to the X-axis, the only time varying component in $\mathbf{r}_k$ is x_k

$$f(\mathbf{r}_k, \mathbf{m}_k) = f(x_k, \mathbf{p}) \quad (5)$$

- Let $\hat{\mathbf{p}}$ be the estimate of $\mathbf{p}$. Then, the Non-linear Least Squares (NLS) cost function gives the following

$$\hat{\mathbf{p}} = \arg\min_{\mathbf{p}} V(\mathbf{p}) \quad (6)$$

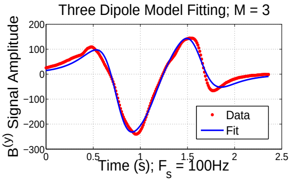
$$\text{where, } V(\mathbf{p}) = \sum_{k=1}^{N} [\mathbf{y}_k - f(x_k, \mathbf{p})]^T [\mathbf{y}_k - f(x_k, \mathbf{p})] \quad (7)$$

Magnetic Dipole Moments and Dipole Separation Algorithm (MDMS Algorithm)

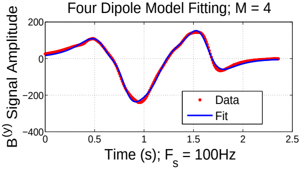
Input: Smoothed Vehicle Magnetic Signature - $\mathbf{a}_{N\times 1}$
Input: The number of magnetic dipoles - M
1: Subtract every $k^{th}, k \in \{1, \ldots, N\}$ sample with the mean of first $N/10$ samples of $a_{N\times 1}$
2: Get the Data Model $\mathbf{a}_k = f(\mathbf{r}_k, \mathbf{m}_k) + \mathbf{e}_k$
3: $V(\mathbf{p}) = \sum_{k=1}^{N} \left[\mathbf{a}_k - f(x_k, \mathbf{p})\right]^T \left[\mathbf{a}_k - f(x_k, \mathbf{p})\right]$, $\mathbf{p}$ be the parameters to estimated and $\mathbf{p} = [\mathbf{m}(i)^T, \Delta X(j), \Delta Y, \Delta Z]^T$
4: Estimate $\mathbf{p}$, $\hat{\mathbf{p}} = \arg\min_{\mathbf{p}} V(\mathbf{p})$
5: Normalized Magnetic Moments $\tilde{\mathbf{m}}(i) = \dfrac{\mathbf{m}(i)}{\|\mathbf{m}(i)\|_2}$

Output: Normalized Magnetic Dipole Moments $\tilde{\mathbf{m}}(i), i \in \{1, \ldots, M\}$; Separation between adjacent dipoles $\Delta X(j), j \in \{1, \ldots, M-1\}$ and $RMSE$ where,
$(RMSE)^2 = \frac{1}{N} \sum_{k=1}^{N} \left[\mathbf{y}_k - f(x_k, \hat{\mathbf{p}})\right]^T \left[\mathbf{y}_k - f(x_k, \hat{\mathbf{p}},)\right]$

Simulation Results



(i) 3-Dipole Model curve fit for a Tata Indica magnetic reading.



(j) 4-Dipole Model curve fit for a Tata Indica magnetic reading.

Sample curve fitting plots for measurements corresponding to a Tata Indica car using MDMS algorithm. $M \in \{3, 4\}$. Sampling Frequency, $F_s = 100Hz$. The error in the fit decreases as number of dipoles increases. Location: IISc Campus

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

M-Dipole	$\Delta X(j)$	$\tilde{\mathbf{m}}(i) = \frac{\mathbf{m}(i)}{\|\mathbf{m}(i)\|_2}$	$RMSE$
3-Dipole	0.474 0.370	$\tilde{\mathbf{m}}(1) = (-0.77, +0.33, -0.52)$ $\tilde{\mathbf{m}}(2) = (+0.26, -0.18, +0.94)$ $\tilde{\mathbf{m}}(3) = (-0.71, -0.19, -0.67)$	19.5
4-Dipole	0.471 0.434 0.001	$\tilde{\mathbf{m}}(1) = (+0.79, +0.29, -0.52)$ $\tilde{\mathbf{m}}(2) = (-0.43, -0.06, +0.89)$ $\tilde{\mathbf{m}}(3) = (+0.35, +0.93, -0.05)$ $\tilde{\mathbf{m}}(4) = (-0.34, -0.93, +0.04)$	12.2

Computation Complexity

- The computational complexity of the NLS cost function using MATLAB function **lsqcurvefit** is $O\{(4M+1)^3\}$. As the number of dipoles increases by 1, the number of parameters to be estimated increases by 4 and so does the complexity.

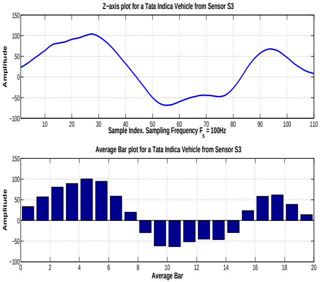
Number of Parameters and $\overline{RMSE}$ for Available Datasets

M-Dipole Model	Size of $\mathbf{p}$ = $(4M+1) \times 1$	$\overline{RMSE}$[‖]
3-Dipole	13×1	7.64
4-Dipole	17×1	5.57

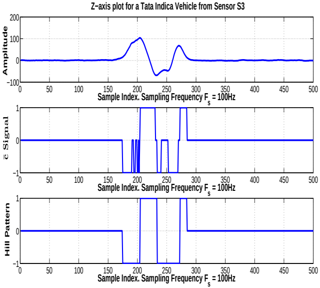
[‖] In order to check the variation of *RMSE* as the number of dipoles *M* increases, we calculate the average *RMSE* for all the datasets '*D*' across different values of *M*.

$$\overline{RMSE} = \frac{1}{D}\sum_{i=1}^{D} RMSE_i \tag{8}$$

Existing Algorithms** for Classification



(k) 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.



(l) 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.

** 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.

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

$$C_R = \frac{1}{I}\sum_{i=1}^{I}\frac{\Omega_i}{L_{ts}} \tag{9}$$

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

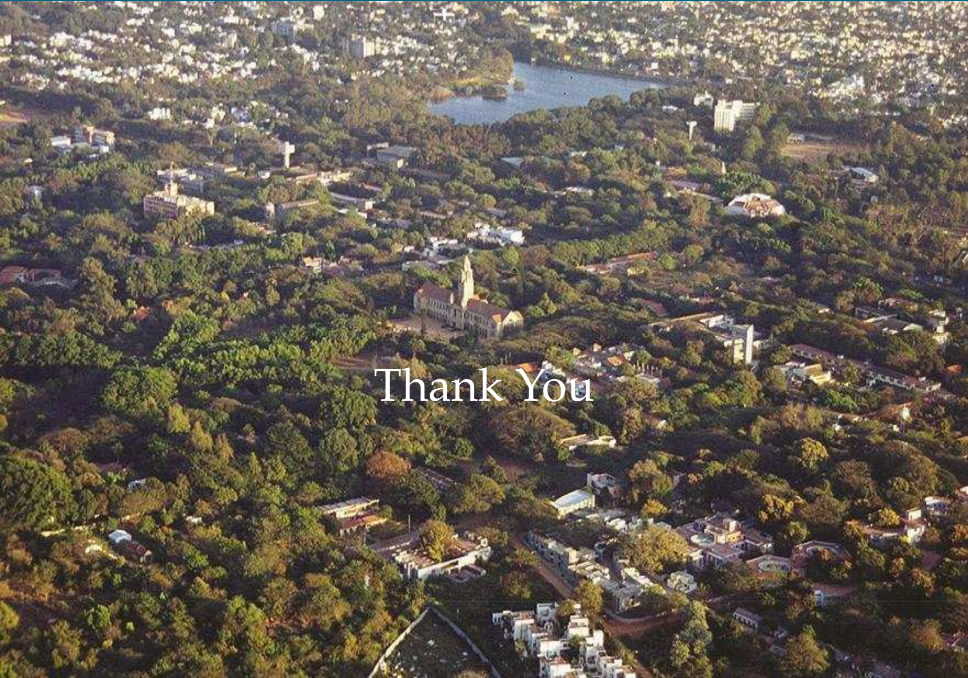
- The goal of a Support Vector Machine(SVM) is to produce a model (based on the training data) which predicts the target value of the test data given only the test data attributes.

Percentage of C_R for **Type 1 vs Type 4** Car for Average Bar, Hill Transform and MDMS Algorithm

Datasets	Feature Extraction Algorithms			
(L_{tr}, L_{ts})	Average Bar Algorithm	Hill Transform Algorithm	MDMS Algorithm 3-DM $\tilde{\mathbf{m}}$	MDMS Algorithm 3-DM ΔX
(70,44)	72.70	76.33	73.80	74.14
(80,34)	73.88	75.39	74.12	74.27
(90,24)	**76.26**	**77.91**	**76.67**	**76.78**

Percentage of C_R for **Type 2 vs Type 3** Car for Average Bar, Hill Transform and MDMS Algorithm

Datasets	Feature Extraction Algorithms			
(L_{tr}, L_{ts})	Average Bar Algorithm	Hill Transform Algorithm	MDMS Algorithm 3-DM $\tilde{\mathbf{m}}$	MDMS Algorithm 3-DM ΔX
(70,50)	57.67	52.33	71.99	72.60
(80,40)	57.54	53.90	73.49	73.45
(90,24)	**58.48**	**51.03**	**74.74**	**74.74**



Thank You