2013 International Conference on Connected Vehicles and Expo (ICCVE)

An Energy-efficient Sub-Nyquist Sampling Method Based on Compressed Sensing in Wireless Sensor Network for Vehicle Detection

Jiangchen Li, Xiaowei Xu, Hongpeng Zhao, Yu Hu*
Huazhong University of Science and Technology
School of Optical Electronic Information
Wuhan, China
bryanhu@hust.edu.cn

Tony Z. Qiu
University of Alberta
Department of Civil and Environmental Engineering
Edmonton, Alberta, Canada
zhijunqiu@ualberta.ca

***Abstract*— The wireless magnetic sensor network is scalable and deployable for traffic surveillance. But active magnetic sensors of the wireless sensor node have high energy consumption which cannot be ignored. It is necessary to save energy of the wireless magnetic sensor node for vehicle detection. In this paper, based on compressed sensing (CS) by random down sampling matrix, an energy-efficient sub-Nyquist sampling method in magnetic sensor network is proposed for vehicle detection. With this new sampling method, the active magnetic sensor's average frequency is less than the Nyquist standard sampling frequency, which reduces the energy consumption of the active sensor, while extending the lifetime of the wireless sensor nodes. When the Compressed Radio (CR) meets the maximum value of 60%, the new sampling method doubles the wireless magnetic sensor node's lifetime and maintains vehicle detection accuracy.**

Keywords—sub-Nyquist sampling; compressed sensing; vehicle detection; wireless sensor network

I. INTRODUCTION

Traffic surveillance systems provide data for Intelligent Transportation Systems (ITS). Most conventional traffic surveillance systems use roadway-intrusive sensors, such as inductive loop detectors, micro-loop probes, pneumatic road tubes, piezoelectric cables and other weigh-in-motion sensors, for high accuracy vehicle detection [1].To maximize the benefits of emerging ITS technologies, all major freeways and local streets must be fitted with real-time traffic controls. However, the installation and maintenance of real-time traffic controls not only disrupts traffic, but also costs approximately $10,000 per intersection. Therefore, these systems are generally too cumbersome and costly for large scale deployment.

Recently, wireless magnetic sensor networks have emerged as a more convenient traffic surveillance system that yields detection accuracy as high as that of inductive loop detectors [2].The sensor networks have greater configuration flexibility, which makes them more scalable and deployable in the traffic network. The availability of data that sensor networks facilitate opens up new opportunities for intelligent traffic operations and control. With a much lower system life-cycle cost than inductive loop, video and radar detector systems, sensor networks are cost-effective for large scale deployment, which may transform the traffic surveillance and control industry.

In the wireless magnetic sensor networks, many methods have been proposed for vehicle detection, such as the threshold slicing algorithm [3], the adaptive threshold algorithm [4][5], the adaptive threshold detection algorithm (ATDA) [1][6] and other methods [7]. Among them, ATDA is key for vehicle detection. Some work [8][9] has been done to improve this method. At the same time, [10][11][12] others have concluded that active sensors in a wireless sensor node have a high energy consumption, which cannot be ignored; therefore, sensor-level energy management strategies have been proposed. However, although there are many sensor-level energy management strategies, including duty cycling [13], hierarchical sensing [10][14] adaptive sampling and model-based active sampling [11][14], none of them can be applied to vehicle detection applications with ATDA because the magnetic signal of moving signals is time-random, short-ranged and different for different vehicles. Thus, for vehicle detection, there is a strong need to manage energy in wireless magnetic sensor networks

In this paper, an energy-efficient compressed-sensing-based sub-Nyquist sampling method for vehicle detection is proposed. The proposed method, with compressed-sensing based on a random down sampling matrix, focuses on reducing the active sensor's average frequency lower than the Nyquist standard sampling frequency, which will save energy. Simulation experiments with magnetic sensor networking are carefully conducted and comparisons between traditional methods and the proposed method are evaluated with a magnetic signal mass of moving vehicles.

II. BACKGROUND

A. *Sensor-level efficient energy management in sensor networks*

Most existing energy management strategies assume that data acquisition consumes significantly less energy than data transmission. However, this assumption is inaccurate in a number of practical applications where the energy consumption of the sensing activity is comparable or even greater than that of the radio [10][11][12]. Hence, several sensor-level energy

*Corresponding author

management strategies have been proposed to prolong the network lifetime.

Duty cycling [13] will make the sensorial system active only for necessary periods to capture required data and power it off in the rest of the periods. This strategy is very efficient when the varying pattern of the captured phenomenon are known in advance. So this strategy .only works for some applications that meet the above acquirement.

Hierarchical sensing [10][14] handles several kind of sensors to capture the same physical quantity, with different accuracy and energy consumption. The final result is a combination of these several kind of sensors. The low-accurate but energy-efficient sensors may be active most of the time, and provide a coarse measurement. When the provided measurement has exceeded the threshold value, an event will be trigged and .the high-accurate but high-energy sensors will be active to get a more accurate result of the physical quantity. This strategy has made a tradeoff between these several kinds of sensors and can be applied to a lot of applications.

Adaptive sampling [11][14] techniques achieves an adaptive sampling rate by utilizing correlations of the stored data and information concerning the available energy. For example, if the quantity of the sensed data changes slowly with time, there is a rather high possibility that the subsequent samples won't differ very much. And the measurements captured by sensors close to each other will not have much difference with each other also. It will make significant reduction of energy consumption taking advantage of these two kinds of correlations: temporal correlation and spatial correlation. And what's more, the available energy can be also taken into consideration to further reduce energy consumption.

Model-based active sampling [11][14] focuses on building a model of the sensed data. Firstly, an initial set of sampled data is required to make such a model. And then the model can be used to predict the following captured data, hence reducing the energy consumption. When the requested data accuracy can't be achieved, the model will be updated to keep pace with the dynamics of the sensed physical phenomenon.

In summary, the magnetic signal of high mobility vehicles is time-random (it is unknown know when the signal will change) and short-ranged (vehicle speed is very fast), and different kinds of vehicles have different signal characters. There is no sensor-level energy management strategy that can be applied for vehicle detection. Hence, there is a strong need for an efficient sensor-level energy management strategy for vehicle detection. To this end, this paper proposes a compressed-sensing-based sensor-level energy management strategy.

B. *Mathematical basics of traditional compressed sensing*

Compressed sensing is a novel sampling method. It exploits the before fact that many signals are sparse or sparse when expressed in the proper basis Ψ [15][16][17][18], such as Fourier orthogonal basis. Based on this, Candes et al. [19][20] proposed the compressed sensing theory. The CS theory offers a method that gathers very few measurements and exactly recovers the signals at acceptable ranges with high probability. There is a mathematical base to CS:

The real original signal x (x is a vector $n\times 1$, $x \in \mathrm{R}^n$) is K-sparse in an orthonormal basis Ψ (such as a wavelet or Fourier orthogonal basis), where the sparse coefficient vector is $\theta = \Psi^{-1}x = (\theta_1, \theta_2, ..., \theta_n)^T$. In CS, a random measurement matrix Φ is used to reduce all original n signals to m measures $y = (y_1, y_2, y_3, ..., y_m)^T$, (y is a vector $m\times 1$):

$$y = \Phi x = \Phi \Psi \theta = \Theta \theta \quad (1)$$

Where Φ is an $m\times n$ measurement matrix (such as random Gaussian), $\Theta=\Phi\Psi$ is a sensing matrix. Restricted Isometry Property (RIP) is used to judge whether or not a particular matrix can be the measurement matrix in CS [16][17][18][19].

The original signal can be exactly recovered at acceptable ranges with high probability by using the Orthogonal Matching Pursuit (OMP) algorithm [18][21][22] to solve the underdetermined linear system:

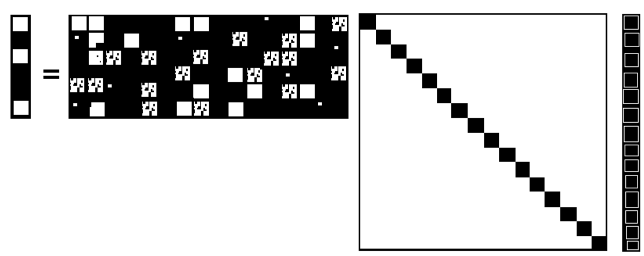
$$\hat{x} = argmin \| x \|_{\ell 1} \quad s.t. \quad y = \Phi x = \Phi \Psi \theta = \Theta \theta \quad (2)$$

Based on traditional compressed sensing, using analog-to-information converter (AIC) [23][24] hardware greatly reduces the information sampling rate; thus, reducing the energy consumption of storage and the communication load. However , the original signal x must be captured in uniform sampling in the Nyquist standard sampling frequency, then use a formula (3) to achieve less measurements [15],

$$Y = \Phi * I * x \quad (3)$$

As Fig.1. shows,

However, because the active sensors achieve signal collection in uniform sampling in the Nyquist standard sampling frequency, this can cause large energy consumption. Therefore, traditional CS is not convenientt in wireless magnetic sensor networks, which this paper focuses on.



Y = Φ * I * x

Fig. 1. Measurement matrix using uniform sampling

III. THE PROPOSED ALGORITHM

A compressed sensing based on random down sampling matrix (RDSM) is proposed.

Aimed at the shortcomings of the traditional CS, a new compressed sensing based on random down sampling matrix was proposed to focus on reducing the active sensor's average frequency compared with the standard Nyquist sampling frequency. This method can reduce the energy consumption of the active sensor and extend the lifetime of the wireless sensor nodes. In this section, the new method will be introduced in detail.

Compared with the uniform sampling based on Nyquist–Shannon sampling theorem in traditional CS, the new method uses a random down sampling matrix (RDSM) to capture the original signal. The sampling matrix was changed from unit sampling matrix (I, $N*N$) to random down sampling matrix (ω, $N*N$). The random down sampling matrix (ω) was marked up by taking out M non-zero values ($M < N$) from the original unit sampling matrix (I, $N*N$). Therefore, in the new compressed sensing method, formula (3) was changed into formula (4),

$$y = \Phi * \omega * x \tag{4}$$

Fig. 2 shows the changing of the sampling method in the two different CS. From Fig. 2, the proposed method changed the active sensors sampling method from uniform sampling into non-uniform down sampling.

The proposed method has a new measurement matrix- $\Phi_{new,}$ as shown in formula (5), which consists of the multiplication of the measurement matrix and the random down sampling matrix ω (see Fig. 3).

$$\Phi_{new} = \Phi * \omega \tag{5}$$

In the traditional compressed sensing theory, to recover the original low error with high probability, the measurement matrix must satisfy the Restricted Isometry Property (RIP) condition [25]. The RIP condition is defined as follows:

Definition [18]: for each integer k = 1,2,…, define the restricted isometry constant (RIC) δ_k of a measurement matrix Φ as the smallest value, such that

$$(1-\delta_k) \| x \|_2^2 \le \| \Phi x \|_2^2 \le (1+\delta_k) \| x \|_2^2 \tag{6}$$

holds for all K-sparse vectors x.

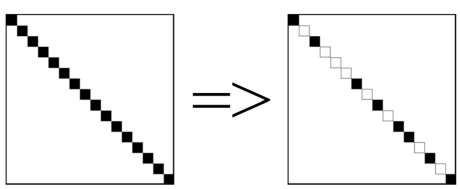


Fig. 2. Formulating uniform sampling into random sub-sampling

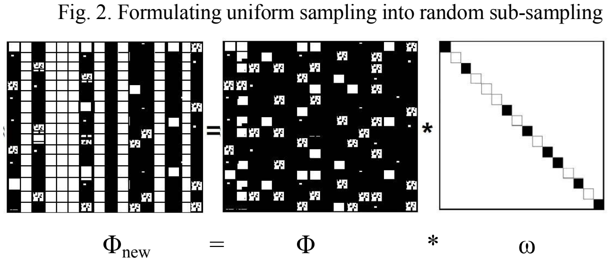


Fig. 3. New computing method of the measurement matrix

The active sensors average sampling frequency is defined as $f_{ave} = M/N$. The number M is determined by the K-sparse and the length N. Because $M<N$, which is described above, the active sensors are down sampling, reducing the active sensors' sampling numbers, and then reducing the energy consumption of the active sensors.

IV. Experimental Results

A. Experimental Settings

To demonstrate the performance difference between the traditional method, the proposed method and the Nyquist-Shannon Sampling method, experiments with magnetic sensor networking were carefully conducted and evaluated with a mass of magnetic signals of moving vehicles.

To obtain signals generated by moving vehicles, wireless magnetic sensor nodes and access points are used. The wireless magnetic sensor consists of a 3-axis digital compass sensor, RISC controller, and an IEEE 802.15.4/RF4CE/Zigbee compliant SOC chip for wireless communications. The radio uses 2.4-Ghz IEEE 802.15.4 compliant RF transceiver at rates up to 250kbps with programmable output power up to 4.5 dBm. The hardware component of the access point is almost the same as the wireless magnetic sensor node, except that it does not have the 3-Axis digital compass sensor.

A wireless magnetic sensor node is used to capture the signals. A magnetic sensor sampled at 128 Hz, which is called full sampling. The full sampling frequency is twice the max frequency of the disturbance of the Earth's magnetic field signal by a vehicle, which satisfies the Nyquist-Shannon Sampling method. Then, the captured signal data is transmitted to the access point by wireless communication. When receiving the original signals, the access point transmits the signals to the host computer via cable transmission.

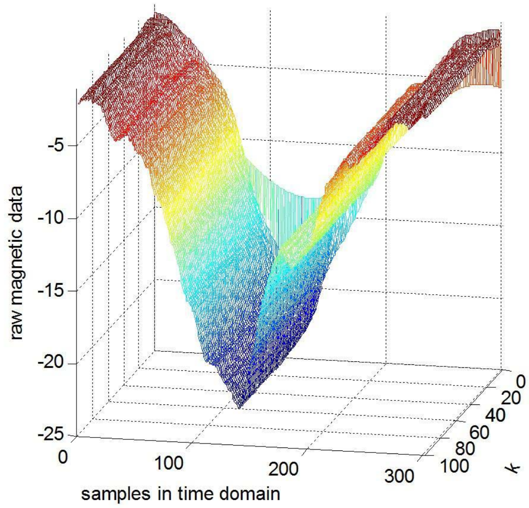
B. Results and Analysis

Simulation and experiment results show that the proposed CS method is a viable energy reduction method for wireless magnetic sensor networks.

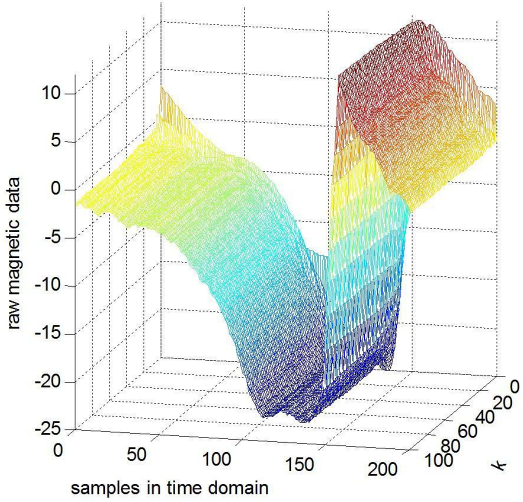
First, the sparse representation of the original magnetic signal captured by active sensors was discussed. Then, the normalized root mean square error (NRMSE) [15][18][20] was compared between the original 128Hz x and recovered signal $\hat{x}$. NRMSE was calculated as the following (7):

$$NRMSE = \| \hat{x} - x \|_2 / \| x \|_2 \tag{7}$$

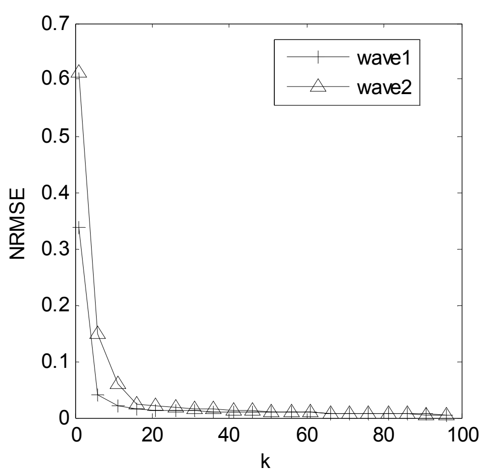
Fig. 4.(a) and (b) show the samples' time domain graph of two signals in different sparse coefficient k. In both figures, when the sparse coefficient k is bigger, then the error of the recovery signal is smaller. Furthermore, as shown in Fig. 4.(c), the two signals have a little NRMSE when sparse coefficient $k \geq 20$.



(a)



(b)



(c)

Fig. 4. Two signals' NRMSE and time domain graph in different sparse coefficient k

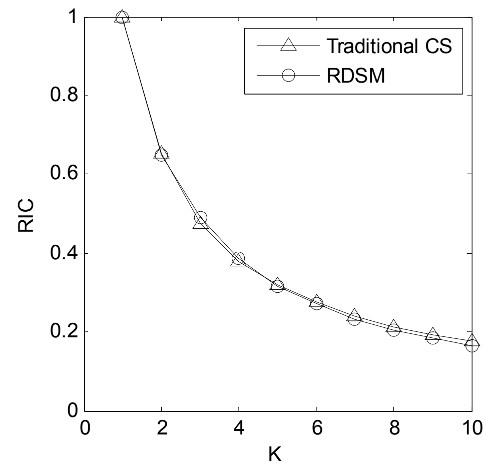
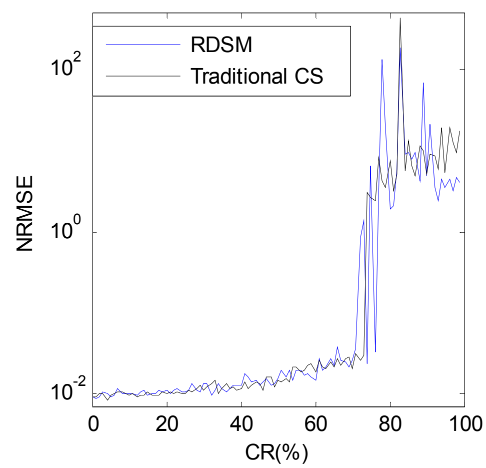
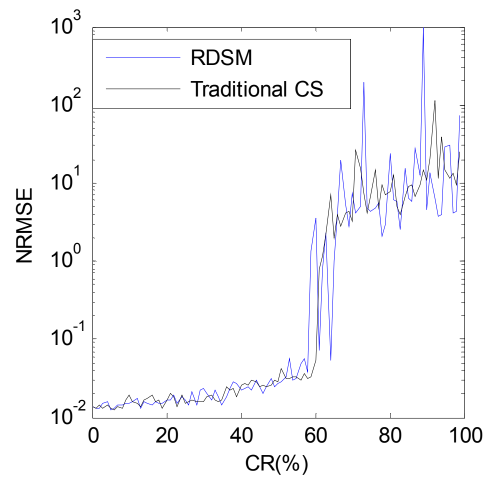


Fig. 5. Comparison of RIC parameters of two matrixes



（a）



（b）

Fig. 6. Two signals NRMSE between traditional CS and new method based on random down sampling matrix which is in different CR (a) signal1 and (b) signal2

In other words, the original signal can be sparse representation in the proper basis Ψ. In this simulation, the signal was sparse in the frequency (Fourier) domains, which means that the original signal can be compressed to a very few measurements and then exactly recovered in great probability using traditional CS.

A new measurement matrix Φ_{new} was verified that satisfies the reconstruction requirement by numerical computation experiments. Fig. 5. shows the comparison of RIC parameters between the traditional measurement matrix ($M*N$ random Gaussian) and the new measurement matrix Φ_{new}, which was calculated by dot product of random Gaussian ($N*N$ random Gaussian) and the random down sampling matrix (M non-zero value).

The results in Fig. 5. show that the new measurement matrix based on random down sampling almost performs as well as the traditional measurement matrix , and also meet the RIP requirements. Therefore, it can be used as a CS measurement matrix and can still recover the original signal, while maintaining the normalized root mean square error at acceptable ranges in big probability. This means that the two methods have the same performance when recovering the original signal.

A recovered signal error and its vehicle detection performance was analyzed. Based on the analysis of the two signals' sparse coefficient k, a proper sparse coefficient k was chosen. Then, the NRMSE of the two signals was analyzed between two methods in different compression ratios. Compression Ratio (CR) = $(1 - M/N)*100\ \%$, that means 60% compressive sampling ratio equals 40% compression ratio. N is the original sampling numbers, M is the compressed sampling numbers. Therefore, the active sensor average frequency is $f = M/N$.

The results (Fig. 6.) show that the new method performs as well as traditional CS. When $CR \leq 60\%$, the new method can recover the original signal and maintain the normalized root mean square error at acceptable ranges.

Furthermore, based on the classical ATDA algorithm [1] , vehicle detection performances are calculated by different CR from recovered signal to original signal. Results in Fig. 7. show that when the reconstruction is not very large, （wave1 CR<75%， wave2 CR<60%）, the proposed method performs as well as the traditional CS and Nyquist-Shannon Sampling (NSS) theorem. However, if the CR increases beyond a certain threshold, the recovered error is too large, so the recovered signal cannot reflect the characters of the original signal, and the ATDA algorithm will fail to detect vehicles.

Lastly, the energy consumption of the novel random down sampling matrix algorithm was analyzed against a 128Hz uniform sampling (Nyquist-Shannon Sampling) theorem. The traditional CS also captures signal in Nyquist frequency. By using the energy consumption calculation formula [26],the difference of lifetime was analyzed between the two sampling methods using a 2400mAh battery. By this way, the current consumption of a wireless magnetic sensor node running random down sampling matrix sampling algorithm and Nyquist Sampling method was measured while acquiring the magnetic signal. The results in Fig. 8. show the significant energy saving performance that the new method offers, where ratio = lifetime(RDSM) / lifetime(NSS). When CR meets the maximum value of 60%, compared with traditional CS and NSS, the new method can extend the node lifetime up to 200%.

It can be concluded that the proposed method performs as well as the traditional CS and the uniform full sampling while extending the wireless sensor node's lifetime.

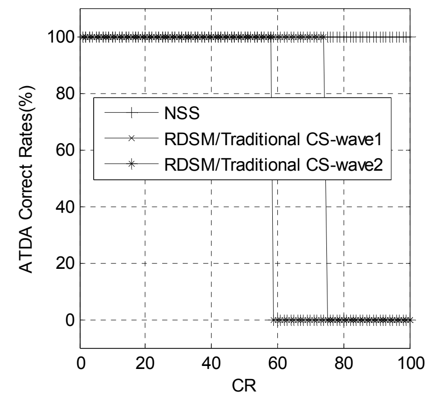


Fig. 7. Vehicle detection using ATDA between three methods in different CR

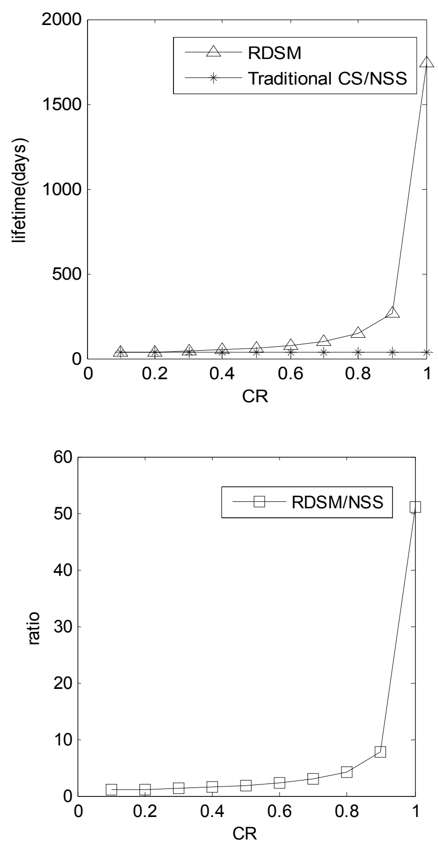


Fig. 8. The different lifetime between two sampling methods

V. Conclusions

This paper presents an energy efficient sub-nyquist sampling method based on compressed sensing (CS) by a random down sampling matrix for vehicle detection. With this sampling method, the active magnetic sensor's average frequency is less than the Nyquist standard sampling frequency, which reduces the energy consumption of the active sensor, while extending the lifetime of the wireless sensor nodes. When the Compressed Radio (CR) meets the maximum value of 60%, the new sampling method doubles the wireless magnetic sensor node's lifetime and maintains vehicle detection accuracy.

VI. Acknowledgment

This work is partially sponsored by National Science Foundation of China (61272070).

VII. References

[1] Cheung S Y, Varaiya P P. Traffic surveillance by wireless sensor networks: Final report[M]. California PATH Program, Institute of Transportation Studies, University of California at Berkeley, 2007.

[2] Cheung S Y, Ergen S C, Varaiya P. Traffic surveillance with wireless magnetic sensors[C]//Proceedings of the 12th ITS world congress. 2005: 1-13.

[3] Cheung S Y, Coleri S, Dundar B, et al. Traffic measurement and vehicle classification with single magnetic sensor[J]. Transportation research record: journal of the transportation research board, 2005, 1917(1): 173-181.

[4] Ding J, Cheung S Y, Tan C W, et al. Signal processing of sensor node data for vehicle detection[C]//Intelligent Transportation Systems, 2004. Proceedings. The 7th International IEEE Conference on. IEEE, 2004: 70-75.

[5] Ding J, Cheung S Y, Tan C, et al. Vehicle detection by sensor network nodes[J]. 2004.

[6] Hostettler R, Birk W. Analysis of the adaptive threshold vehicle detection algorithm applied to traffic vibrations[J]. Sort, 2011, 20(50): 100.

[7] Knaian A N. A wireless sensor network for smart roadbeds and intelligent transportation systems[D]. Massachusetts Institute of Technology, 2000.

[8] Yang B, Zou F Q. A novel approach for vehicle flow detection by using anisotropic magnetoresistive sensor[J]. Journal of Zhejiang University. Engineering Science, 2011, 45(12).

[9] Bohui H, Hong H, Kefu C, et al. Power Efficient Vehicle Detection Algorithm Using Wireless Magnetic Sensor Node[J]. Journal of Data Acquisition & Processing, 2007, 3: 016.

[10] Alippi C, Anastasi G, Di Francesco M, et al. Energy management in wireless sensor networks with energy-hungry sensors[J]. Instrumentation & Measurement Magazine, IEEE, 2009, 12(2): 16-23.

[11] Raghunathan V, Ganeriwal S, Srivastava M. Emerging techniques for long lived wireless sensor networks[J]. Schott B, Bajura M, Czarnaski J, et al.

[12] Schott B, Bajura M, Czarnaski J, et al. A modular power-aware microsensor with> 1000X dynamic power range[C]//Information Processing in Sensor Networks, 2005. IPSN 2005. Fourth International Symposium on. IEEE, 2005: 469-474.

[13] Kim N, Choi S, Cha H. Automated sensor-specific power management for wireless sensor networks[C]//Mobile Ad Hoc and Sensor Systems, 2008. MASS 2008. 5th IEEE International Conference on. IEEE, 2008: 305-314.

[14] Anastasi G, Conti M, Di Francesco M, et al. Energy conservation in wireless sensor networks: A survey[J]. Ad Hoc Networks, 2009, 7(3): 537-568.

[15] Candes E, Romberg J. Sparsity and incoherence in compressive sampling[J]. Inverse problems, 2007, 23(3): 969.

[16] Akçakaya M, Tarokh V. A frame construction and a universal distortion bound for sparse representations[J]. Signal Processing, IEEE Transactions on, 2008, 56(6): 2443-2450.

[17] Boufounos P, Baraniuk R. Quantization of sparse representations[R]. RICE UNIV HOUSTON TX DEPT OF ELECTRICAL AND COMPUTER ENGINEERING, 2007.

[18] Candès E J, Wakin M B. An introduction to compressive sampling[J]. Signal Processing Magazine, IEEE, 2008, 25(2): 21-30.

[19] Candès E J. Compressive sampling[C]//Proceedings oh the International Congress of Mathematicians: Madrid, August 22-30, 2006: invited lectures. 2006: 1433-1452.

[20] Donoho D L. Compressed sensing[J]. Information Theory, IEEE Transactions on, 2006, 52(4): 1289-1306.

[21] Tropp J, Gilbert A C. Signal recovery from partial information via orthogonal matching pursuit[J]. 2005.

[22] Sha W. Orthogonal Matching Pursuit Algorithm[OL]. http://www.eee.hku.hk/~wsha/, 2013-4.

[23] Mallat S G, Zhang Z. Matching pursuits with time-frequency dictionaries[J]. Signal Processing, IEEE Transactions on, 1993, 41(12): 3397-3415.

[24] Kirolos S, Ragheb T, Laska J, et al. Practical issues in implementing analog-to-information converters[C]//System-on-Chip for Real-Time Applications, The 6th International Workshop on. IEEE, 2006: 141-146.

[25] Baraniuk R, Davenport M, DeVore R, et al. A simple proof of the restricted isometry property for random matrices[J]. Constructive Approximation, 2008, 28(3): 253-263.

[26] Sensys Networks Group Authors. Battery life analysis of the sensys networks wireless vehicle detection system[M]. ARRB Consulting/La Trobe University, 2007.