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ADMM-Driven Data Recovery for Reliable Vehicle Counting in Iot-Based Wireless Sensor Networks

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Abstract
In the context of IoT-based applications, Wireless Sensor Networks (WSNs) are integrated into the Automatic Vehicle Counting (AVC) systems for the purpose of advanced traffic management. As with many other applications, sensor node dropout, data transmission issues, and noise from the environment can lead data loss in WSN, which affects the precision of vehicle detection. We suggest the use of the data recovery framework that combines signal processing methods with the Alternating Direction Method of Multipliers (ADMM) for data reclamation in WSN-based AVC systems. Compressed sensing (CS) techniques ensure that less data is sent over the network and increases the efficiency of data retrieval. Total Variation (TV) regularization enforces signal smoothness constraints, Non-Local Means (NLM) Filter performs noise reduction, and both wavelet transformation and multi-resolution analysis are applied for signal denoising.Incorporating ADMM into the framework as an optimization engine allows for the iterative refinement of the recovered signal by the ADMM framework while ensuring data accuracy and preservation of the signal structures. As is shown in the experiments, the algorithm maintains high accuracy even with missing or degraded sensor readings. Improved precision in vehicle counting is achieved, especially in noisy and low-resource wireless environments. The framework is shown to enhance the router integrity in IoT systems and provides solutions for real-time data issues in traffic monitoring systems.

Index Terms: ADMM, WSNs, IoT, AVC, Signal processing, CS, TV, NLM, Wavelet transform

INTRODUCTION

Traffic is a popular concern faced by city dwellers worldwide. The increasing number of vehicles coupled with rapid development of urban areas has caused immense traffic congestion in cities globally. Internet of Things technology is being used more and more for real-time traffic management and monitoring in intelligent transportation systems (ITS). One of these systems is Automatic Vehicle Counting (AVC), which uses Wireless Sensor Networks (WSNs) for vehicle monitoring and traffic density analysis in order to optimize traffic control systems.

The exploitation of Wireless Sensor Networks (WSNs) in AVC systems faces several challenges. Sensor node failures, weak wireless connections, environmental impacts, and hardware inadequacy can lead to data loss, which degrades the overall data quality. Such an impact makes AVC systems less effective due to the diminished vehicle counting accuracies. There is, therefore, an urgent requirement for

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the data recovery techniques to be designed for the predictive models to free reclaim the continuous monitoring of the data sensor for AVC systems.

To tackle this problem, we propose an innovative data recovery approach based on ADMM that applies sophisticated signal processing methods to repair missing or corrupted information in Wireless Sensor Networks (WSNs). This approach integrates Compressed Sensing (CS) to minimize the data transmission burden, Total Variation (TV) regularization to promote the reconstruction of smooth signal slices, Non-Local Means (NLM) filtering to suppress noise based on the self-similarity of images, and Wavelet Transform for decomposition and feature extraction at multiple scales. The problem of data recovery is formulated as a composite recovery problem, which is efficiently solved using the ADMM (Alternating Direction Method of Multipliers) as the optimization method.

This research illustrates the positive impact of using ADMM in combination with signal processing techniques on recon- struction accuracy, noise resilience, bandwidth, and computation resource efficiency. The method is tested using simulations on MATLAB, and the results indicate potential for implementation in real-time Automatic Vehicle Classification (AVC) systems within intelligent traffic management systems.

RELATED WORKS

Sensor-based systems within IoT applications have made it possible for technologies such as Wireless Sensor Networks (WSNs) to offer data recovery features. Enhanced data recovery using optimization techniques and signal processing has been the focus of several studies amidst challenges posed by sensor node failures and environmental interferences.

Yang et al. in [1] proposed a data recovery solution in WSNs using the ADMM neural network architecture. Their solution showed optimization algorithms are capable of being unrolled into deep learning models, thus, effectively reconstructing lost or corrupted signals. Liu et al. [3] built on this by proposing ADMM-ResNet, which offers guaranteed convergence and high accuracy during WSN data recovery. These works accepted and explored the possibility of using ADMM as a distributed and scalable optimization method in sensor networks, further expanding on the learning models discussed in the former papers.

The application of Compressed Sensing (CS) to WSNs to lower the quantity of data required to be sent has been instrumental in preserving the primary framework of the signal. ADMM has proven to be effective in solving sparse recovery problems, as highlighted by Boyd et al. in [7] leveraging the technique's ability to decompose a large and complex problem into smaller ones that are solvable in distributed systems. In addition, the use of Total Variation (TV) minimization techniques have helped in preserving smooth transitions during the reconstruction of signals.

The Non-Local Means (NLM) filtering method focuses on image denoising and uses redundancy in data and averaging similar patches across a signal. Due to its capability in preserving intricate details and reducing random noise, NLM is widely adopted in medical imaging and in traffic monitoring [2]. We would also like to mention wavelet-based methods of denoising, which have also been recognized for retrieving and preserving multiscale feature as well as high frequency noise in [5].

Focusing on the application side, various vehicle counting techniques based on WSNs have been proposed. For instance, Singh et al. [10] developed an integrated real time AVC system using infrared and a camera for traffic control in metropolitan areas. Other researches [12][13] proposed IoT based traffic control systems with active vehicle identification and intelligent signal control. A common weakness in these systems is that they all assume that the data from sensors of the system are sent reliably and completely which is not the case in real life scenarios.

Prior works have been done on individual techniques like signal enhancement using CS, TV, NLM, Wavelets and optimization using ADMM. However, to date, there has not been any formal proposal on integrating these techniques with the framework designed specifically for AVC in WSNs.

CONEPTUAL LEARNINGS

A. Thoery:

1) IoT-based traffic management: IoT (Internet of Things) is a technology that deals with the connection of a wide range of devices/systems/ processes that involve the Internet.
2) AVC (Automatic Vehicle Count): This is an active method that is suggested in the paper [6] which counts the vehicles that are passed through a junction using sensors that click hundreds of pictures in some period which is considered the data that need to be modified and send to the main server for the further processing.
3) The steps of signal processing techniques that were followed in this paper are CS, TV, NLM, and Wavelet analysis. At last, ADMM is used for enhancement.

B. Signal Processing & It's Types

Now we try to understand the Signal processing technique, what are the different signal processing techniques that we are going to use in this paper, and also how ADMM works for the data recovery of WSNs. Signal processing techniques work on the analysis and modification of signals. These techniques are mainly used for obtaining data which is very important for the networks and which need to be modified. The data mainly consists of images, videos, and audio, which are encoded in signals. There are many fields where these signal-processing techniques can be used, some of them are audio and image processing, telecommunication, medical imaging, and radar.

C. Automatic vehicle classification

It classifies different types of vehicles using technologies like computer vision and Artificial intelligence. In-situ sensors are the sensors that are installed directly on or in the roadway, such as inductive loop detectors, pneumatic road tubes, and piezoelectric sensors. These sensors detect the number of vehicles as well as measure their speed and length. Radar sensors can be used to detect the presence and movement of vehicles, even in low-visibility conditions.

1) Compressed Sensing (CS) : Compression, the word itself means the compression of the data using little measures. It compresses the signals by exploiting its signal sparsity and yet it can be reconstructed faithfully and accurately.
2) Total Variation (TV) : Total variation is a signal processing technique that is mainly used for image processing. It is a noise-removal technique. It is based on the principle that signals with excess spurious details have high TV. That is the image gradient magnitude is high. By this technique, we can reduce the total variation of the signal which can lead to the denoising of the image. Here in this paper, we use this technique as we are using camera sensors to take pictures in the process of AVC.
3) NLM (non-local mean): NLM is also used for denoising the image or noise reduction. Right after TV, we can use NLM to optimize or reduce more noise which can be more accurate in recovering the data. In NLM instead of looking at just neighboring pixels, it calculates the mean intensity within similar patches inside the image. This technique of NLM uses the advantage of similar images to reduce the noise in the image. It is used widely for image processing as mainly it is used for medical purposes for

improved diagnosis.

4) Wavelet Analysis : This method mainly focuses on the element of analyzing the signals and breaking them into time- frequency components. Using this method of Wavelet transforms, the mathematical transforms can transmit with various frequencies at the same time. This analysis is mainly important for stationarity signals with a transient property like speech, seismic data, or economic time series. It is processed by dividing a signal into a basic wavelet and then providing the details about how it varies with time and frequency and also identifying it with certain characteristics or irregularities. Wavelet analysis is a method that is applicable in image denoising, compression, and pattern recognition and therefore is useful in almost all the parts of Signal processing.

D. ADMM

The ADMM is a strong optimization tool that is used in the solving of convex optimization problems. ADMM is widely used in many fields, in this paper we are mainly concentrating on signal processing. Its main motto is to divide a complicated problem into simpler ones, solve each simple problem, and then at last converge the solutions and find the ultimate solution through its iteration methods. To solve a signal processing problem using ADMM we reduce its application into an optimization problem of minimizing a target function which includes regularization terms and data fidelity. The problem is divided into smaller problems using ADMM where each problem relates with the particular term of the objective function. These divided subproblems are easier to solve than to solve the main problem.

Usually, ADMM iteration involves 3 key steps:

1) Adjust a Lagrange multiplier
2) Updating of the variables that are associated with the regularization term.
3) Finally update the terms related to the data fidelity term. Then this process heads towards convergence. The ADMM algorithm is useful for many different applications like image denoising, image reconstruction, and sparse signal recovery. The main advantage of ADMM is that it solves complicated large-scale optimization problems without taking lots of computer time. It is used in Gaussian and Poissonian image restoration problems. The benefit of ADMM is that it is an intuitive interpretation.

METHODOLOGY

This section describes the steps of the proposed ADMM (Alternating Direction Method of Multipliers) based data recovery framework for Automatic Vehicle Counting (AVC) via Wireless Sensor Networks (WSNs). The methodology applies multiple techniques of signal processing ADMM to optimize and accurately recover the erased, noisy, or incompletely captured data from the sensor data.

A. Problem Overview

In AVC systems based on IoT, sensor nodes capture data on vehicles incessantly, relaying the raw data to a processing unit (cloud or edge node). The data may, however, be lost or degraded for IoT-based AVC systems owing to sensor malfunctions, rough environmental conditions, and data transmission issues. The focus of the proposed method is on recovering the vehicle count data at its highest possible accuracy the data is estimated at based on its structure and sparsity.

B. Proposed Framework

The recovery pipeline consists of the following sequential stages:

- **Data Collection:**

Infrared and magnetic sensors are examples of wireless sensors used to gather vehicle activity signals in real-time. The vehicle activity signals are sampled to create a sparse representation of vehicle activity.

The raw signals, however, face the challenge of environment and network-related factors, leading to capture noisy or incomplete data.

- **Preprocessing and Compressed Sensing (CS):**

In order to decrease the load of data transmission across the network, Compressed Sensing (CS) is employed. CS exploits the sparsity of the signal to allow representation with fewer measurements. A sensing matrix A is used to compress the signal x into a measurement vector y as: $y = AX$ This method offers crucial information while enabling efficient transmission.

- **Total Variation (TV) Regularization:**

Total Variation (TV) minimization is performed after CS on the compressed signal.
The TV minimization problem is defined as follows:

$$TV(x) = \sum |x_i - x_{i-1}|$$

TV is efficient in diminishing the unnecessary fluctuations of the signal while preserving the significant edges.

- **Non-Local Means (NLM) Filtering**:

To improve the signal even more, Non Local Means (NLM) filtering is used, which cuts down noise. NLM filtering is different from the local filtering methods. NLM achieves the denoised value of a given data point through a weighted average of similar patterns throughout the signal. This method is effective in combatting noise in weak and sparse data areas.

- **Wavelet Transform**:

The signal undergoes Wavelet Decomposition after performing TV and NLM filtering to achieve multiscale analysis. This stage splits the signal into low-frequency (approximation) and high-frequency (detail) components. The wavelet coefficients facilitate further denoising and feature extraction.

- Denoising is performed by applying a threshold to the high-frequency coefficients.
- To reconstruct the filtered signal, Inverse Wavelet Transform is applied.
- This improves the recovered signal's temporal resolution and structural accuracy.
- **ADMM Optimization**:

The last and most important step is utilizing the ADMM to deal with the overall optimization problem. ADMM divides the complex recovery problem into a set of simpler subproblems, each of which can be solved and analyzed independently. The objective function summarizes data fidelity, sparsity, and smoothness. We solve the following optimization problem using ADMM:

Where:

$$\min_{x} \|y - Ax\|^2 + \lambda \cdot TV(x) \quad \text{subject to} \quad x \geq 0 \quad (1)$$

- y is the observed compressed data,
- A is the sensing matrix,
- x is the signal to be recovered,
- λ is a regularization parameter controlling the trade-off between fidelity and smoothness.

The Alternating Direction Method of Multipliers (ADMM) is used to solve this problem by iteratively updating:

- the signal estimate x,
- the auxiliary variables z (to separate terms),

- the dual variables u (scaled Lagrange multipliers),

until convergence is reached. This leads to an optimized, denoised, and sparse reconstruction of the original signal.

Final Output Extraction:

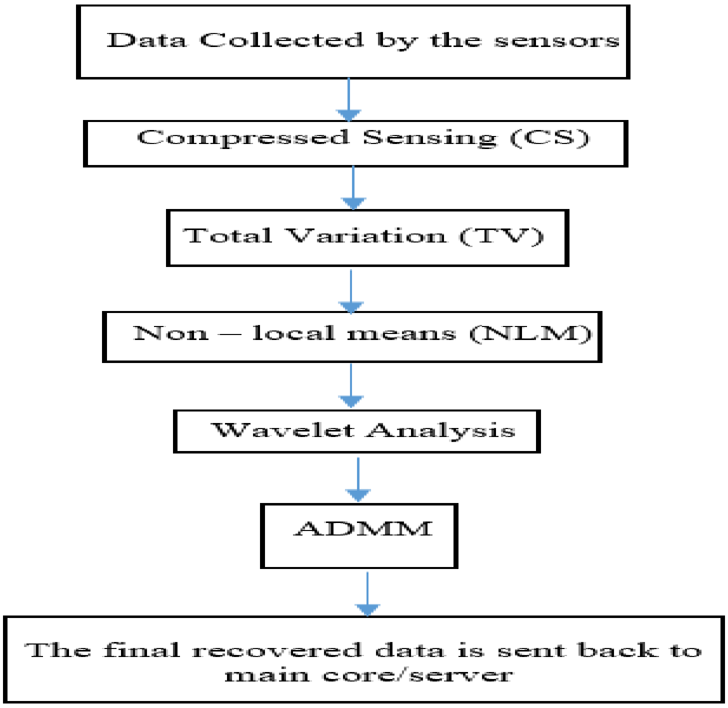

Fig. 1. PROCESS FLOWCHART

Post ADMM, the output is generated with high confidence as a refined estimate of the original vehicle count signal. The resulting data is available for visualization, analysis to be used by other systems for traffic predicting or adaptive managing traffic-light systems.

MATH APPROACH

The math approach to this paper includes the equation from different signal processes and also their explanation for this method

1) Problem Formulation: Minimize the

$y - A * x2 + \text{lambda} * TV\,(x)$

Subject to:

x greater than 0

y: The sensor measurements A: The sensing matrix

x: The sparse signal representing vehicle counts TV(x): Total variation regularization term lambda : Regularization parameter Explanation:

1) The objective aim is to minimize the reconstruction error between the sensor measurements y and the product of the sensing matrix A and the sparse signal x.
2) The second term, lambda*TV(x), calculates the total variation regularization on the signal x, which ensures the piecewise smoothness and sparsity.
3) The constraint x 0 suggests that the estimated vehicle counts are non-negative in the data collected.

Compressive Sensing (CS):: Minimize:
Subject to: $y=A*x$
L1 norm of the signal, promoting sparsity:
y: Measured data A: Sensing matrix
|x||_1
Explanation: The CS problem calculates a sparse signal x by solving the L1-norm minimization according to the measured data y being a linear combination of A and x.

2) Total Variation (TV) Regularization:
$TV(x) = |x\_i - x\_(i-1)|$
x_i: values of the signal 'x' Explanation:
TV regularization promotes sparsity by calculating the sum of absolute differences between adjacent elements in the signal x, ensuring piecewise constant signals.

3) Non-Local(NLM) Denoising:
denoised_image(i) = w(i, j) ∗ noisy_image(j)

- denoised_image(i): Denoised value at position 'i'
- w(i,j): Weight of pixel 'j' concerning pixel 'i'
- . noisy_image(j): Noisy value at position 'j'.

Explanation:
NLM denoising adds the denoised value at each pixel as a weighted average of the noisy pixel values and with weights based on the similarity between local patches around each of the pixels.

4) Wavelet Signal Processing: x_wavelet= WaveletTransform(x)
SSx_wavelet: Wavelet coefficients of the signal 'x'. Explanation:
Wavelet transform decomposes the signal into the high-frequency(detail) and low-frequency (approximation) components, providing a multi-resolution representation of the data.

- Alternating Direction Method of Multipliers (ADMM): x: Primary Variable
- z: Auxiliary Variable
- u: Scaled Lagrange multiplier
- rho : Penalty parameter Explanation:

The augmented Lagrange, L(x, z, u), includes the data fidelity term
$||y - A * x||\hat{2}$
TV regularization, and a penalty term for the difference between 'and 'z'.
ADMM alternates between optimizing x, z, and u while keeping other variables fixed in each iteration until convergence.

Fig. 2. Sensor description

CODING APPROACH

The code part for solving this optimization problem is formulate using MATLAB which significantly shows the graph of data recovery of the vehicle count that is collected in AVC.

A. Code explanation

This MATLAB code is defined for solving the optimization problem using the optimization algorithm. The provided algorithm reduces the cost function. The main purpose of the function defined in the code is to compare the data that is reconstructed at the end of the process and the sensed data, and then push for sparsity in that data of signal. There's a part in the code where it tries to smooth out the signal too. This code works by updating three variables namely x, z1, and z2 until it reaches convergence.

The main part of this code involves proximal operators which forces L1 norm and TV regularization terms. The lamba1 and lamba2, z1 and z2 are multipliers that ensure that the x is sparse enough and has the regions that are smooth enough according to the L1 and TV norms. These multipliers are controlled by hyperparameters.

The x changes from each iteration using these proximal operators. Using these proximal operators, we can shrink elements into very zero sizes (which promotes sparsity) while enforcing the smoothness at the same time. The values of z1 and z2 update themselves. z1 update itself by the difference between x and b and then z2 update itself by the equation Dx + Tx minus x.

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```matlab
% Parameters
n = 100; % Number of sensors
m = 50;  % Number of measurements
rho = 1; % ADMM parameter
max_iterations = 100; % Maximum number of iterations
lambda_tv = 0.1; % Weight for the TV term
lambda_cs = 0.1; % Weight for the consistency term

% Generate random data
A = randn(m, n); % Sensing matrix
x_true = randn(n, 1); % True data
b = A * x_true; % Noisy measurements
% ADMM Algorithm
x = zeros(n, 1); % Initialize the data vector
z = zeros(n, 1); % Initialize the auxiliary variable
u = zeros(n, 1); % Initialize the dual variable

for k = 1:max_iterations
    % Update x
    x = (A' * A + rho * eye(n) + lambda_tv * eye(n)) \ ...
        (A' * b + rho * (z - u) + lambda_tv * z - lambda_cs * ones(n, 1));

    % Update z
    z = max(0, x + u);

    % Update u
    u = u + x - z;
end
% Plot the recovered data
figure;
subplot(2, 1, 1);
bar(x_true);
title('True Data');
xlabel('Sensor Index');
ylabel('Data Value');
subplot(2, 1, 2);
bar(x);
title('Recovered Data');
xlabel('Sensor Index');
ylabel('Data Value');
```

Fig. 3. code on matlab

B. Theory and explanation

The output graph consists of the data that is collected over sensors and also recovered data.

The objective function includes terms for sparsity, data accuracy, and also smoothness. It mainly aims at the reconstruction of signals or images from limited or noisy data.

The data fidelity term makes sure of the reconstructed signal which is x, whether it closely matches the observed measurements

b. Now minimizing the distance between Ax and b will result in a solution that fits the available data.

The sparsity of the process is encouraged through the regularization of the difference operator applied to x through L1. This sparsity first pushes many coefficients to zero and also selects key features 2w removing unimportant details.

The total variation regularization of x results in piecewise smoothness. The total variation gauges to gradient magnitude and also favors piecewise constant regions with slow variation at edges. This edge-preserving technique has many applications in smoothing images while retaining their important boundaries and contours.

The Proximal operators and also Lagrange multipliers are used in an iterative process to optimize the formed objective function. The Lagrange multipliers z1 and z2 help in satisfying the regularization, while Proximal operators enforce the smoothness constraints and sparsity constraints. The convergence occurs after a set number of iterations or threshold accuracy. The end sparsity of representation, fidelity to measurements, and smoothness balanced by reconstructed x. This type of framework is also applied in the field of medicine for medical imaging, and also for deblurring of the photographs and more – where

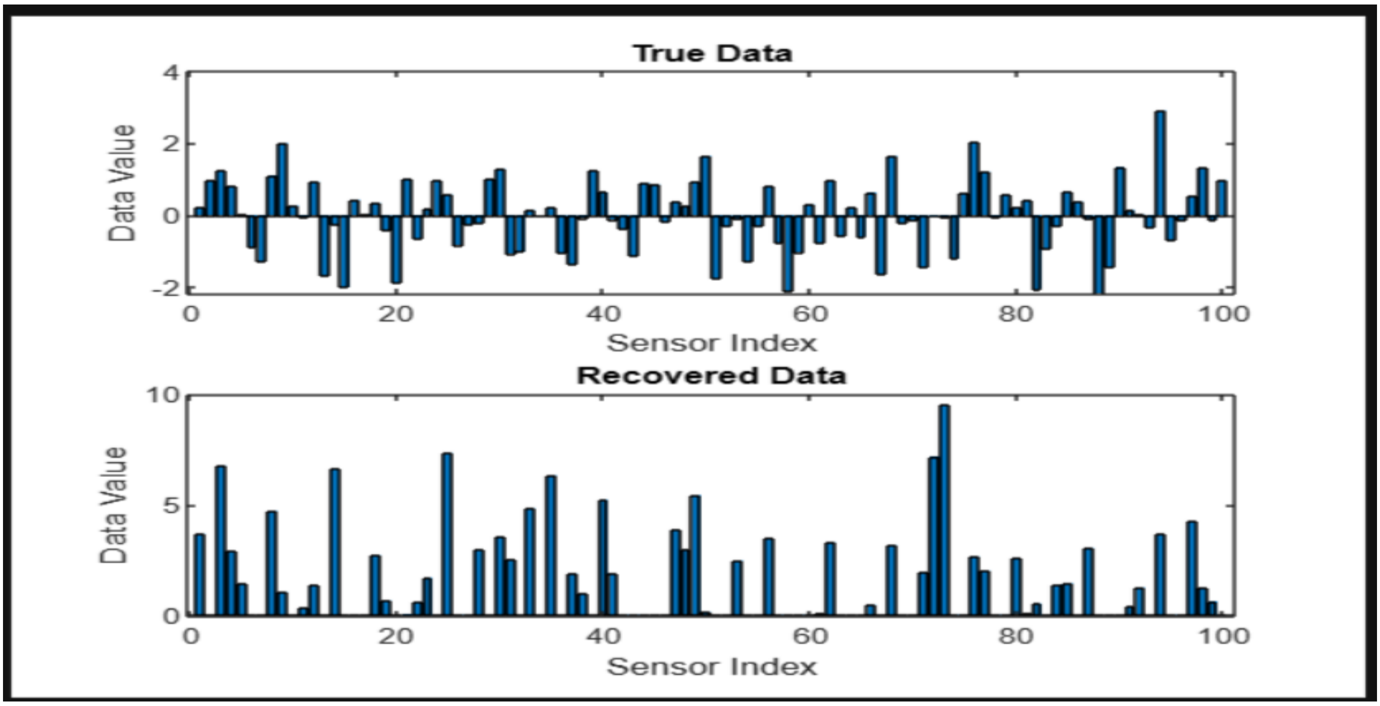
there is a need for high-quality signal recovery from limited data. The sparsity versus smoothness emphasis is determined
by regularization weights lambda1 and lambda2.
Real-world Deployment and Testing: Test the suggested approaches, in implementations, such as smart urban areas, industrial automation, or environmental surveillance. Assess the system's efficiency, scalability, and dependability, in real-life scenarios.
The expected output is a graph with sensor values as an index and the data recovery expectancy is also mentioned.
The sample output or the expected output can be expressed in a tabular form for the example usage.

TABLE I REAL TIME VEHICLE COUNT

Table	**Table Column Head**		
ITERATION	X	Z1	Z2
0	[0,0,0]	[0,0,0]	[0,0,0]
1	[0.1,0.2,0.3,0.4]	[0.05,0.1,0.15]	[0.01,0.02,0.03]
2	[0.18,0.25,0.31]	[0.08,0.15,0.19]	[0.015,0.03,0.04]
3	[0.22,0.28,0.32]	[0.09,0.14,0.17]	[0.018,0.028,0.03]
4	[0.24,0.29,0.33]	[0.1,0.13,0.15]	[0.02,0.026,0.028]

FUTURE RELATED WORKS

This paper includes several complex areas of research on the Wireless sensory network data collection for IoT traffic Management through sensor nodes using the method of AVC and recovering the data using signal processing techniques of CS, TV, NLM, Wavelet transform, and the main method of optimization which is ADMM.
In the future the ADMM algorithm can be extensively improved for non-convex optimization problems. Even the Compressed sensing technique can be widely improved by the reconstruction quality of sparse sensor data.
The security and privacy aspects can be very challenging and there is a high scope for improvement in this sector in the future. For standardization and interoperability in ADMM. The data recovery techniques, in traffic management, will simplify the integration of the devices or systems to ensure smooth interoperability.
In the future this methodology can be useful to the public by developing a live website, web app or mobile app in which the information inferred from this can be uploaded in the app by the server which will be available for the public on live, which can save a lot of time.



CONCLUSION

The integration of ADMM-based data recovery in WSNs and advanced signal processing techniques CS, TV, NLM, and Wavelet Analysis is a promising approach for the improvement of IoT-based traffic management using AVC. It enables efficient data reconstruction, and real-time processing. However, there needs to be careful measuring in implementing this approach in real life as there can be many computational resource issues. The above experimental results prove how data can be actively recovered from WSNs for AVC in wireless networks. In this paper, the type of algorithm that is proposed is, it will reduce the amount of data that needs to be transmitted over the wireless network and also increase the accuracy of vehicle counting. Researching and implementing advanced CS techniques, such as structured sparsity , to enhance the reconstruction quality of sparse sensor data. Developing signal processing methods that are energy-efficient for IoT devices. In conclusion, the overall proposed ADMM-based data recovery algorithm in this paper is an accurate way of approach for recovering lost data and also improving the performance of the sensors that are assigned for automatic vehicle counting.

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