The Application of Sparse Representation for Classification Problems on Wireless Sensor Networks

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ABSTRACT

This research will focus on applying the sparse representation for classification problems on wireless sensor networks, which includes the topics about acoustic classification, the transmission data size reduction and indoor radio frequency based localization accuracy improvement. Sparse representation is applied for increasing the performance of the acoustic classification and radio tomographic imaging(RTI). This work also investigates how to fit the computationally expensive into the resource constrained wireless sensor networks.

General Terms

Algorithms, Design, Experimentation, Performance

Keywords

ℓ_1 minimization, sparse approximation, audio classification, Wireless Sensor Networks (WSNs), indoor localization

1. INTRODUCTION

My research work includes two topics about the application of sparse representation for classification problems on wireless sensor networks.

In the first research work, we use Sparse Approximation for Wireless Acoustic Sensor Networks(ASNs). We address a number of challenges to make Sparse Approximation Classification(SAC) possible on resource constrained ASN nodes. Applying compressive sensing theory, the signal for classification can be compressed by the muliplication of a random matrix.

The second research work aims for applying sparse representation for radio tomographic imaging, which can be modelled as a classification problem. Sparse representation is used for increasing the localization accuracy.

2. THESIS STATEMENT

2.1 Real-time Classification in Acoustic Sensor Networks

Acoustic Sensor Networks (ASNs) have a wide range of applications in environmental monitoring. In-network classification is critically important in ASNs because wireless transmission costs several orders of magnitude more energy than computation [1]. The main challenges of in-network classification in ASNs include effective feature selection, intensive computation requirement and high noise levels. To address these challenges, we propose a sparse representation based featureless, low computational cost, and noise resilient framework for in-network classification in ASNs. The key component of Sparse Approximation based Classification, ℓ_1 minimization, is a convex optimization problem, and is known to be computationally expensive.

2.1.1 *Sparse Representaion for Acoustic Sensor Nerworks*

We propose greedy column reduction method to reduce the size of the dictionary, so as to fit SAC for in-network classification in ASNs. Figure 1 shows even only using 10% elements in the dictionary, the method keeps the high accuracy. Our evaluation using real-life datasets shows that the proposed SAC framework outperforms conventional approaches such as Support Vector Machines (SVMs) and k-Nearest Neighbor (kNN) in terms of classification accuracy and robustness(shown in Figure 2). The signal in energy spectrum domain also can be compressed by the multiplication of a random projection for classification, which speeds up the computation and does not decrease the classification performance.

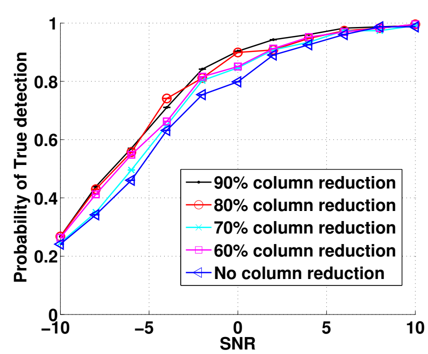

Figure 1: SNR vs accuracy for greedy column reduction method

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SenSys'13, November 11–15, 2013, Roma, Italy.
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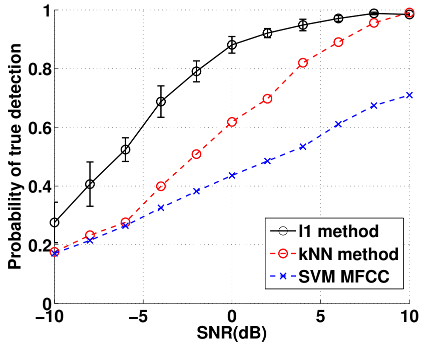

Figure 2: SNR vs accuracy for ℓ_1 method, $k$nn and SVM

2.1.2 *Experiment in Real Environment*

We also evaluate the performance of the proposed SAC on an outdoor wireless ASN testbed. The testbed, which is located on our campus with thin vegetation, consists of five nodes configured as *Ad-hoc* mode with a star network topology. The aim of the experiments is automatic bird vocalization recognition. We choose two bird species that are frequently observed on our campus: cockatoos and rainbow lorikeets. The experiment is a multi-class classification with 3 classes: the calls of cockatoos, the calls of rainbow lorikeets and environmental noise (which includes the sound all other birds, crickets etc.).

The nodes in our ASN testbed are based on the Pandaboard ES, a single board computer costing US$182, which has a 1.2GHz ARM Cortex-A9 with 1GB of RAM and a 4GB SD-card. Pandaboard also features an 802.11 interface for wireless communication, and runs Ubuntu Linux distribution. Each node hosts 2 USB ports, one of which connects to a USB microphone. The microphones are configured to sample at 24kHz. The accuracy of our SAC is 70.17%.

2.1.3 *Energy-Saving Embedded Sensor for Acoustic Classification*

We also investigate to use energy-saving embedded sensor for acoustic classification. Sensor nodes first sample the interesting sound, then perform Fast Fourier Transformation(FFT) online to calculate the energy spectrum distribution of the acoustic sample. Second, sensor nodes apply the random projection on the energy spectrum vector to minimize the size of the vector. Our work in Section 2.1.1 already shows classification performance using sample after random projection can be as good as that without projection. Figure 3 shows the acoustic sensor, which uses ST's ARM Cortex-M3-based STM32L ultra-low-power MCU, 48KB RAM, also with a Microphone whose sample rate is up to 10kHz.

2.2 Application of Sparse Represenstation for Radio Tomographic Imaging

2.2.1 *Introduction of Radio Tomographic Imaging*

Radio Tomographic Imaging(RTI) is a localization technology, which can be used for ehealth and age care industries. The simple radio-based sensor nodes are deployed for locating objects. There are two advantages of RTI. First, it

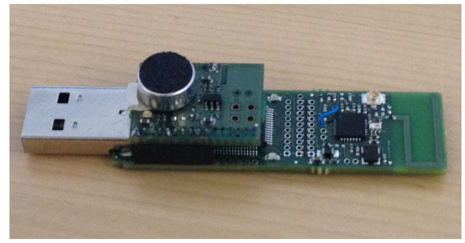

Figure 3: Energy-saving embedded sensor

is a device free localization, which means the monitored objects do not need to wear any device on them. Second, there is no need for RTI to conduct training before localizaion. After the object is in the monitored area, it blocks the links between the transmitters and receivers, which causes RSS variance. The attenuation is exploited for determining the location of the object. Figure 4 shows the example of RTI.

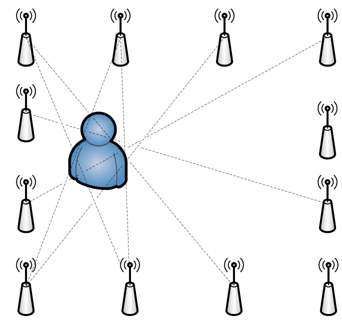

Figure 4: The example of RTI

2.2.2 *The application of Directional Attenna for Radio Tomographic Imaging*

We investigate to use a directional antenna named SPIDA, which stands for SICS Parasitic Interference Directional Antenna, shown in figure 5. This SPIDA smart antenna is operated in 2.4GHz ISM band with Tmote Sky device using a CC2420 radio. SPIDA antenna has 6 direction totally, so each direction occupies 60 degree, and it also can be configured as omni-directional.

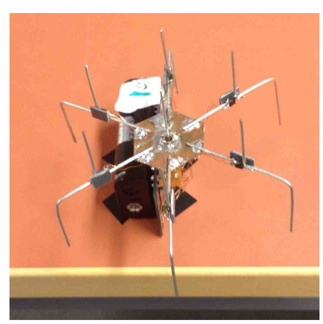

Figure 5: The photo of SPIDA

Figure 7 shows a clear advantage of SPIDA compared with the omni-directional antenna in terms of the RSS variance when the link is attenuated. The direction 1 of SPIDA faces the sender, RSS of the first direction drops significantly when the link is attenuated by objects, while the omni-directional antenna does not reduce largely.

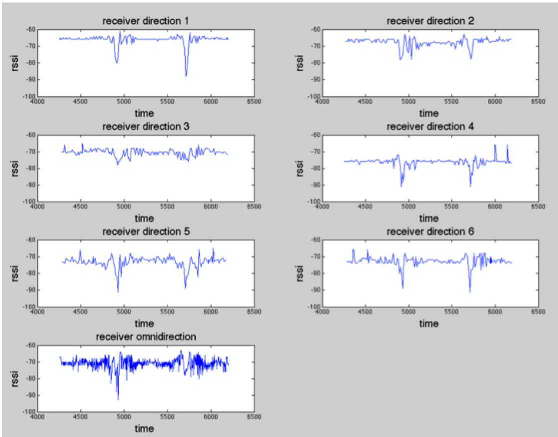

Figure 6: RSS variance comparation between the directional antena and omni-directiona antenna

However, there are still several challenges for this research topic. The first one is the shadow fading. The complexity of the indoor environment cause the attenuation which affects the signal, and this influence is varied with time and unpredicted. Second, not like outdoor environment, the indoor facilities result in the multi-path propagation, which makes signal noisy.

The SPIDA can be useful for anti-fading. The antenna gain of SPIDA varies as an offset circle from approximately 7 dB to -4 dB in the horizontal plane, and the highest gain is shown in the selected direction. The character of SPIDA can be used for looking for the antenna pattern pair(s) which can help for increase the performance of RTI.

2.2.3 The application of Sparse Representation for Radio Tomographic Imaging

The RSS variance as indicators can be used for localizing the persons in the monitored area. If there is only one or two persons in the monitored area, only several voxels are occupied. To determine whether each voxel is occupied or not is a classification problem.

The RTI can be modelled as linear expression problem, which gives the opportunities for sparse representation to show better performance. Sparse representation may also help for device-free multi-subject counting problem. Motived by compressive sensing theory, it gives the chance for the sensing nodes to send less data by projection matrix, which is also a potentially interesting topic.

Figure 7 shows the difference between use the sparse representation (ℓ_1) classifier, mean-based RTI [5] and variance-based RTI [6] .

3. RELATED WORK

Recently, researchers have proposed classification methods for resource constrained environment according to these characteristics of WSNs [3, 2].

In terms of RTI, Wilson etc. propose attenuation-based RTI [5] and variance-based RTI [6], they also suggest regularization method for RTI [4].

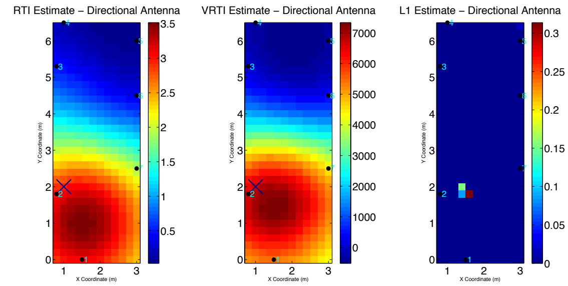

Figure 7: Localization results using mean-based RTI, variance-based RTI and L1 RTI

4. CONCLUSION

In our research, the application of sparse representation is investigated for two classification problems, i.e. acoustic classification in embedded networks and radio tomographic imaging using directional antenna.

In the first work, we propose a novel featureless, efficient and robust SAC framework for ASNs. In particular, in order to make the computationally expensive SAC method feasible for ASNs, we propose a column reduction algorithm to significantly reduce the size of the training dictionary. As for the second, we intend to apply the directional antenna SPIDA for anti-fading and sparse representation for increasing the localization accuracy.

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Biography.

Bo Wei is a third year Ph.D student in the University of New South Wales, Australia. His supervisor is Prof. Chun Tung Chou in the School of Computer Science and Engineering, the University of New South Wales, and his co-supervisor is Dr. Wen Hu, who is working at CSIRO Computational Informatics as a principal research scientist. From April to November 2013, he was also a visiting Ph.D student in Swedish Institute of Computer Science supervised by Prof. Thiemo Voigt. Bo Wei's expected date of dissertation submission is August 2015.