Logo detection and recognition using CNN

by

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ABSTRACT

LOGO DETECTION AND RECOGNITION USING CNN

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Thesis supervisor: Senior Lecturer MSc. Konstantin Latuta

Keywords: Logo detection, Logo recognition, Computer Vision, Machine Learning, Convolution Neural

Network, Classification, Recurrent Neural Network, Pattern Recognition, Object Recognition, Data aug-

mentation

Logo detection and recognition continues to be of great interest to the document retrieval community as it

enables effective identification of the source of a document. This paper contributes the design of the system

able to detect the logo of any product from the documents and images after that recognize it from the archive

via the convolutional neural network. For detecting and recognize of logos implemented via convolutional

neural network, which creates initial classification to determine the presence of the logo on the document

or image. As regards to the former, a collection of logos was designed and implemented to train the classier,

to identify and to extract the logo features which were eventually used for logo detection and recognition.

The latter regards the detection of logos from an input image. In particular, the experimental study aimed

to detect if the input image contains one or more logos and to decide which logos are contained.

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ACKNOWLEDGEMENTS

I thank the merciful and all-knowing, for sparing my life in sound health and giving me the opportunity to accomplish this thesis.

I wish to express my deepest gratitude to my supervisor Senior Lecturer MSc. Konstantin Latuta for his guidance, advice, criticism, encouragement and insight throughout the research.

I am highly indebted to my parents for their encouragement, support and unlimited love.

Finally, i wish to extend a special thanks to my colleagues for their valuable support and company. They really made my life a fabulous one.

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LIST OF SYMBOLS/ABBREVIATIONS

MSE Mean-square-error

CNN Convolutional neural network

RNN Recurrent Neural Network

CV Computer Vision

ML Machine Learning

LRT Learning Rate

Convolutional layer

Pool Pooling layer

ReLU Rectified Linear Unit

Softmax Normalized Exponential Function

Sigm Special case of logistic function

INTRODUCTION

1.1. Overview

Here will be overview of all my project [2], [3].

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1.2. Related Work

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PROBLEM STATEMENT AND THESIS ORGANIZATION

2.1. Introduction

This chapter states the specific challenges that are mostly encountered in logo detection and logo recognition and our possible solution to overcome and solve some of challenges and problems. Below briefly explained the available methods and their consequence and then our most possible solutio.

2.2. Statement of the Problem

Among the various applications of adaptive filtering techniques, echo cancellation is well known to be the most tricky one. This is so because its explicit nature represent a lot of challenges for any adaptive filter. There are quite a lot of issues related to this crucial application, among which a few are as follows. First, it is well known that the echo paths can have excessive lengths in time, e.g., up to or even more than hundreds of milliseconds. For instance, in network echo cancellation, the usual lengths are in the range between 32 and 128 milliseconds, while in acoustic echo cancellation, these lengths can be even higher [7]. As a result, long length adaptive filters are readily required (with hundreds or even thousands of coefficients), affecting the convergence rate of the adaptive algorithm. Alongside, the echo paths are time-variant systems, requiring efficient tracking abilities for the echo canceller. Second, the undesired echo signal is usually combined with the near-end signal; conceptually, the function of the adaptive filter here is to segregate this mixture and offer an estimate of the echo at its output along with an estimate of the near-end from the error signal. This is quite a difficult task since the near-end signal may include either or both the background noise and the near-end speech; this noise can also be variant and powerful while the near-end speech can be like a big disturbance. Also, the input of the adaptive filter is a times speech sequence, which is a time-varying and highly correlated signal that can affect the whole performance of adaptive algorithms. In addition, the echo path is sparse in nature, requiring adaptive algorithms with good sparsity exploitation properties.

Over the paste decades, numerous types of adaptive filters have been used for echo cancellation. The normalized least-mean-square (NLMS) algorithm is one of the most popular among them, due to its numerical stability and moderate computational complexity. However, its use of a uniform step-size across all filter

coefficients limits its convergence speed when estimating a sparse signal [16]. To overcome this problem, Duttweiller in [7] proposed a proportionate updating technique by assigning different step-sizes across filter taps independently to promote sparsity exploitation. Other approaches for sparsity exploitation apply subset selection scheme during the filtering process through statistical detection of active taps or sequential partial updating [34], [35]. However, both of these approaches are somewhat tricky and computationally complex whose performances degrade with the variation of sparseness level of the echo path. In addition, the aforementioned techniques fail to provide a satisfactory performance in a high correlated environment. The problem of identifying sparse echo paths has gained increasing interest due to the recently introduced framework of Compressive Sensing (CS) [26], [30], [32]. As a result, the LMS algorithm was modified to exploit sparsity property of a signal by employing l_0 -norm or l_1 -norm constraint into the cost function of the standard LMS [22], [29], [36], [37], [38]. The norm constraints accelerate the convergence of small active taps for identification of sparse echo path. Unfortunately, the resulting modified LMS filters suffer from the norm constraint adaptation during filtering process and produce estimation bias for identifying systems with a variety of sparseness levels due to lack of adjustable factor. To limit the estimation bias and enable the quantitative adjustment of the norm constraint adaptation, a non-uniform norm constraint (NNCLMS) was proposed in [40] which employs a p-norm like constraint to modify the cost function of LMS filter. The main challenge of this approach is its inability to maintain its performance when the input signal is highly correlated such as speech signal [41]. The variable step-size LMS (VSSLMS) was proposed by Harris et. al. [42] to stabilize the performance of the conventional LMS, but still has limited ability to exploit sparsity of the system due to its no use of sparsity characteristics [43], [56].

2.3. Our Contributions

In this thesis, we propose a new approach of identifying a sparse echo path. The proposed approach will be shown to overcome some of the above mentioned limitations. The approach combines a VSSLMS and a p-norm constraint. The variable step-size portion stabilizes the sparse system when the input signal is correlated where as the p-norm constraint exploits the system's sparsity by imposing a zero attraction of the filter coefficients according to the relative value of each filter coefficient among all the entries which, in turn, leads to an improved performance when the system is sparse. It would be shown to have a superior performance compared to the conventional approaches. We also carry out the convergence analysis and establish a stability condition of the proposed algorithm. The performance of the proposed algorithm is compared with diverse l_1 -norm and p-norm based sparse adaptive filters in AEC settings using two noise types; Additive White Gaussian Noise (AWGN) and Additive Correlated Gaussian Noise (ACGN) and

using acoustic echo paths of length N=256 and N=512 respectively. Also, the performance of the proposed algorithm has been extensively investigated in other sparse systems with a variety of sparseness degree. Simulation results demonstrate that the proposed algorithm outperforms different l_1 -norm and p-norm based sparse filters in a sparse system identification.

2.4. Thesis Organization

The structure of the thesis is organized as follows:

- In Chapter 3, a general review of the most important adaptive filters used for echo cancellation application is presented.
- In Chapter 4, the proposed algorithm is presented. A review of the VSSLMS algorithm and a broad concept of the *p*-norm constraint are provided. The mean square convergence analysis and a stability criterion of the proposed algorithm are also carried out and presented.
- In Chapter 5, an experimental study is provided in order to compare the performance of the proposed filter with other l_1 -norm and p-norm based sparse adaptive filters in the context of AEC.
- In Chapter 6, conclusions and a discussion on possibilities for future work are provided.

REVIEW OF DEEP LEARNING AND PATTERN RECOGNITION ALGORITHMS

3.1. Introduction

This chapter provides a brief review of the well known sparse adaptive filters used for echo cancellation. Firstly, we present the proportionate-based adaptive algorithms as background for estimating a sparse impulse response, we then subsequently discussed the zero attracting sparse adaptive filters used in the field due to their robustness and efficiency in performance. These filters operate based on l_1 -norm optimization such as used in CS techniques [26] rather than proportionate updating based approach [7].

3.2. Computer Vision and Pattern Recognition

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3.3. Image Segmentation Methods

3.3.1. Thresholding

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3.3.2. Clustering Methods

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3.3.3. Compression-based methods

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3.3.4. Histogram-based methods

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3.3.5. Edge detection

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3.3.6. Dual clustering method

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3.4. Supervised Learning

3.5. Optimization

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3.6. Backpropagation

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3.7. Neural Networks

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3.7.1. Vanilla Neural Networks

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3.7.2. Convolutional Neural Networks

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3.7.3. Recurrent Neural Networks

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3.7.4. Capsules Neural Networks

3.8. Summary

PROPOSED METHOD

4.1. Introduction

This chapter provides a brief review of the well known sparse adaptive filters used for echo cancellation. Firstly, we present the proportionate-based adaptive algorithms as background for estimating a sparse impulse response, we then subsequently discussed the zero attracting sparse adaptive filters used in the field due to their robustness and efficiency in performance. These filters operate based on l_1 -norm optimization such as used in CS techniques [26] rather than proportionate updating based approach [7].

4.2. Review of Pipeline

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4.2.1. Object Segmentation Method

4.2.2. Logo Recognition Training Framework

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4.2.3. Logo Recognition Testing Framework

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4.3. Review of Logos Dataset

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4.4. Concept of Technologies and Frameworks

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4.5. Summary

SIMULATION RESULTS

5.1. Introduction

This chapter provides a brief review of the well known sparse adaptive filters used for echo cancellation. Firstly, we present the proportionate-based adaptive algorithms as background for estimating a sparse impulse response, we then subsequently discussed the zero attracting sparse adaptive filters used in the field due to their robustness and efficiency in performance. These filters operate based on l_1 -norm optimization such as used in CS techniques [26] rather than proportionate updating based approach [7].

5.2. Logos Dataset Preparing

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5.3. Checking Image Segmentation and Object Proposal

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5.4. Experiments on Training CNN

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pharetra lobortis. Donec molestie tortor eu lectus accumsan ultrices. Cras suscipit turpis quis tellus laoreet, sit amet cursus velit volutpat.

5.5. Evaluating CNN Performance for Segmented Images

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5.6. Application Creating

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5.7. Summary

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CONCLUSIONS AND FUTURE WORK

6.1. Conclusion

In this thesis, Some of the challenges caused by undesired acoustic echoes that occur in communication devices are addressed. The research concentrates on the development of a new adaptive filtering algorithm that enables us to identify the sparse echo path of the acoustic room system. Some of the available sparse adaptive algorithms have been reviewed. A new *p*-norm constraint adaptive algorithm has been proposed. The convergence analysis of the proposed algorithm has been presented and its stability condition is derived. The performances of the proposed algorithm have been investigated through extensive simulation experiments and evaluated in terms of the convergence rate and MSD estimate.

An acoustic echo path of fixed sparsity was simulated in AWGN and a better MSD estimate of the proposed algorithm compared to the best performer among the NLMS, PNLMS, IPNLMS, NNCLMS, ZA-LMS and RZA-LMS algorithms is obtained. Where as in the ACGN, it has been noticed that, even with highly correlated Gaussian noise, the proposed algorithm still much better than the other algorithms in terms of convergence rate and/or MSD. The NLMS, PNLMS and IPNLMS algorithms failed to provide good performance compared to NNCLMS, RZA-LMS and ZA-LMS algorithms. This is due to their lack of available parameters to effectively track sparse impulse responses.

The proposed algorithm was furtherly investigated in identifying an unknown system having a variety of sparsity ratios (ranging from 75%, 50% and 25% sparsity ratios). It has been shown to be performing more robust than the NNCLMS, RZA-LMS and ZA-LMS algorithms in both AWGN and ACGN environments. This is due to the virtue of the variable step-size parameters in addition to p-norm constraint associated with the proposed algorithm.

6.2. Further work

Despite the fact that the results of this work are adequate and satisfactory, there still other works which need to be conducted in the future in order improve the quality of this approach. All our investigations on the performance of the proposed algorithm are limited to only two types of noise environments; AWGN and ACGN. Therefore, one of possible future works could be investigating its performance in other types of noise environments such as additive white impulsive noise, additive correlated impulsive noise, etc. Another area of investigation could be applying the proposed algorithm in other scenarios different from echo cancellation, such as channel equalization, adaptive beam forming, etc. In addition, the performance of the proposed algorithm may also be inspected using a longer length echo paths of about 1024 coefficients and greater.

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