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FINAL YEAR PROJECT

Robust Speech Detection in High Levels of Background Noise

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Declaration of Authorship

I, Marcin Baginski, declare that this thesis titled, 'Robust Speech Detection in High Levels of Background Noise' and the work presented in it are my own. I confirm that:

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- Where I have consulted the published work of others, this is always clearly attributed
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Abstract

Department of Electrical and Electronic Engineering

MEng Information Systems Engineering

Robust Speech Detection in High Levels of Background Noise

by Marcin Baginski

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I would like to thank ...

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Chapter 1

Introduction

1.1 Voice Activity Detection

Voice Activity Detection (VAD) is a process of identifying parts of an audio recording which contain the presence of human voice as opposed to those which are only comprised of silence or the background noise. VAD is a relatively simple task in recordings which have high signal-to-noise ratios (SNR), in which voice can be distinguished from noise simply by computing the short-time energy of all frames and setting an appropriate threshold for their classification. However, in real applications, the signal is almost always corrupted to some extent by background noise which makes the VAD performance to deteriorate. VAD decision is especially difficult for the unvoiced phonemes [1] whose spectrum contains no periodicity and is often similar to the one of white noise [2].

There has been an active research in the VAD area from as early as 1975, when Rabiner and Sambur [3] proposed a VAD algorithm (then referred to as "algorithm for determining the endpoints of isolated utterances") based on the aforementioned short-time energy and the zero-crossing rate. This approach worked reasonably well for signals with SNR on the order of 30 dB, however since then there has been a need for much better performance, including applications where algorithm robustness has to be achieved even at negative SNRs. Recently, numerous VAD approaches have been proposed, based on various features such as

1.2 Applications of VAD

VAD is often the first step in many signal processing applications including speech recognition [4–8], speech coding and transmission [4, 9–12], speech enhancement [4, 13, 14], noise estimation [4] or speaker recognition [15]. In most applications the noise-robust VAD decisions reduce the computational load required by the system and improve its accuracy. The reduced computational load is achieved since the voice-inactive frames are often not processed at all. At the same time, the clear boundaries of an utterance help to improve the accuracy of some systems (e.g. speech recognition).

1.2.1 Automatic Speech Recognition

In Automatic Speech Recognition (ASR), it is of importance to first extract the voice-active parts of a signal which can then be passed to the actual recognition module. This procedure increases both the accuracy of the ASR system as well as its speed, since the recognition task is not performed on the parts of the signal which do not contain speech. A sample block diagram of an ASR system which uses a VAD module is presented in Figure 1.1 [4]. For ASR, and also most other applications, it is crucial for the VAD module to be able to identify all speech segments in order not to degrade the accuracy of the entire ASR system. Therefore, VAD systems often implement a fail-safe approach which means that if there is an uncertainty in classification of a frame, it is safer to label it as speech than otherwise. Typically, there is a trade-off in VAD performance which can be characterised as maximising the precision while keeping the recall at a steady, high rate.

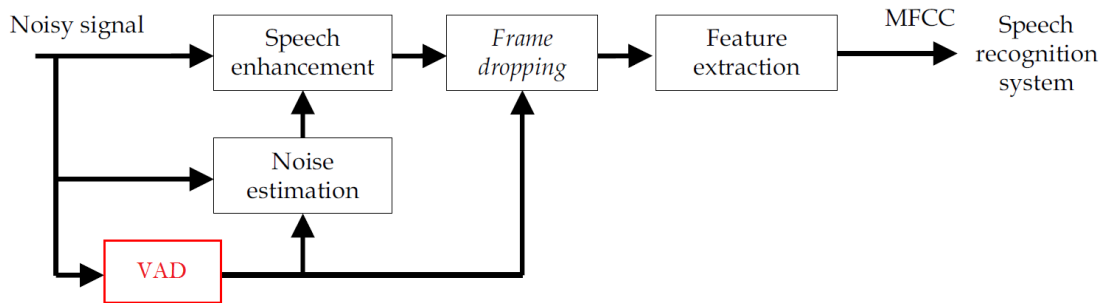


FIGURE 1.1: Block diagram of an Automatic Speech Recognition system with Voice Activity Detection module [4]

1.2.2 Speech Coding and Transmission

A typical phone conversation involves each person speaking on average no more than 50% of the time [12]. Using this fact it can be concluded that signal transmission would be greatly optimised if each transmitter was switched-off half of the time. Such approach could cause the overall system capacity to double. The technique of interrupted transmission during periods of silence is known as discontinuous transmission (DTX). In order to work properly, it requires a precise Voice Activity Detection to direct the operation of a transmitter between being switched on or off. As an alternate method to stopping the transmission, a dual-mode encoding technique could be employed, which uses a higher bit-rate for coding the voice-active frames and lower for silence/noise. The latter is precisely what the popular ITU-T G.729 Annex B [11] standard does, transmitting the voice-active parts at a fixed bit rate of 8 kb/s while the noisy ones at only 15 b/frame.

Figure 1.2 shows a structure of a dual-mode coding and transmission system, in which the VAD module is used to direct the incoming signal into either the active or inactive speech encoder. The noise can be either transmitted at a much lower bit-rate or the transmission might be switched off completely. In case of a stopped transmission, the receiving end often implements a *comfort noise* [4, 11, 12] generation module, which creates a synthetic signal similar to the background noise at the transmitter so that the listener does not notice the rapid, inconvenient switching during the conversation.

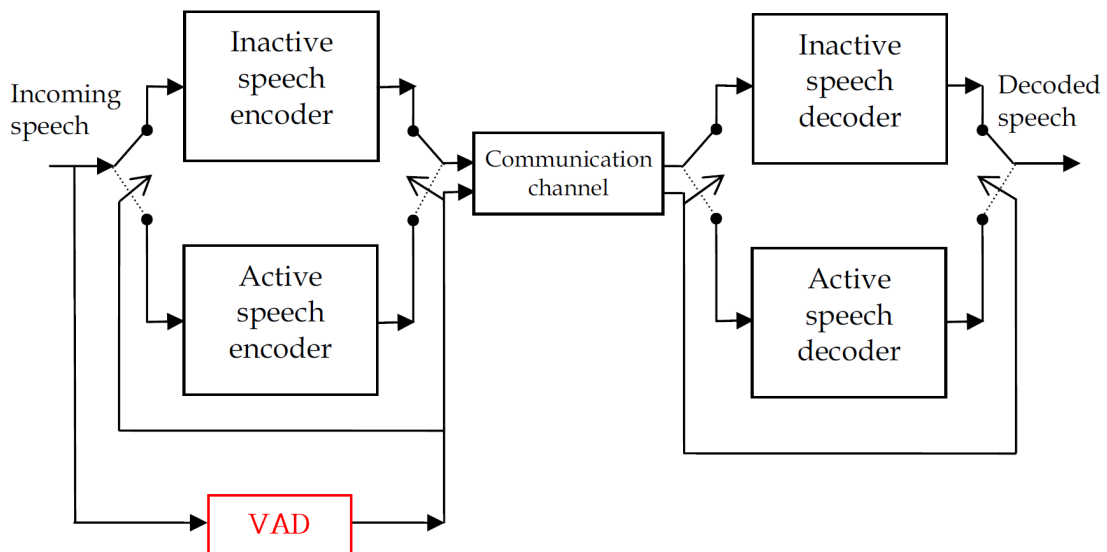


FIGURE 1.2: Block diagram of an dual-mode transmission system with Voice Activity Detection module [11]

1.2.3 Noise Estimation and Speech Enhancement

Speech enhancement aims to improve the intelligibility and quality of speech signals corrupted by additive noise of some kind. Many speech enhancement systems use a technique called *spectral subtraction* [1, 4]. It assumes, that the clean speech can be represented in the frequency-domain in the form:

$$|S(f)| = |Y(f)| - |N(f)| \quad (1.1)$$

where $|Y(f)|$ is the amplitude spectrum of the corrupted speech, $|S(f)|$ of the clean speech and $|N(f)|$ of the noise. In order for this technique to work, the noise needs to be additive, stationary and uncorrelated with the clean speech signal. Additionally, one needs to estimate the spectrum of the noise, which in real-world applications where a variety of different, often nonstationary, noise types are encountered, is a nontrivial problem. A robust Voice Activity Detector can become very useful in this task by identifying the voice-inactive frames of a signal from which the noise statistics could be estimated. A precise VAD can also become useful in applications dealing with slowly varying piecewise stationary noises, where the noise statistics can be adaptively estimated based on the most recent VAD decisions.

1.3 Structure of a typical VAD system

Figure 1.3 shows a high-level structure of a Voice Activity Detector, however only the two middle blocks are considered a core of a typical VAD system.

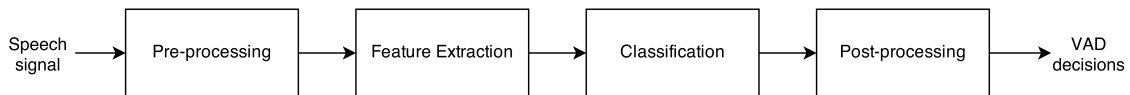


FIGURE 1.3: Block diagram of a typical Voice Activity Detection system

1.3.1 Pre-processing

Describe pre-processing

1.3.2 Feature Extraction

Describe feature extraction

1.3.3 Classification

Describe classification

1.3.4 Post-processing

Describe post-processing

The noisy speech signal is passed to a pre-processing module which might perform a variety of tasks, including noise suppression in order to improve the performance of the actual VAD algorithm. Additionally, during pre-processing the signal is often split into frames which are typically 20-100 ms long. In the next step, a number of features is calculated for each frame. These can be time-domain, frequency-domain, cepstral-domain features or other, depending on the specific VAD algorithm. The extracted information is passed to a classification module, which makes a decision whether to label each frame as speech or non-speech. The classification can be based on a variety of decision rules, starting from simple thresholding to more advanced methods such as machine learning or statistics. The last block, post-processing, often tries to *smooth* the VAD decisions in order to reduce the number of false positives and false negatives. For example, if among 50 consecutive frames, each of 20 ms duration, only one is classified as speech, the post-processing module might change the decision for this particular frame, since it is highly unlikely for speech to be active during such short-time window.

1.4 Thesis organisation

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