Real Time Implementation of Voice Activity Detection based on False Acceptance Regulation

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Abstract: In speech compression systems, Voice Activity Detection (VAD) is frequently used to distinguish active voice from other noisy sounds. In this paper, a robust approach of VAD is presented to deal with non-stationary noisy environments. The proposed algorithm exploits adaptive thresholding technique to keep a desired False Acceptance (F_A) rate. Iterative hypothesis tests, using signal energy, are implemented to discard or to accept the successive audio frames as active voice. According to the stationary property of the speech, we provide a smoothing method to obtain final VAD decisions. The main contribution of the proposed algorithm concerns its ability to automatically adjust the energy threshold according to the local noise estimator. We analyzed the proposed approach by presenting a comparison with the G.729-B via the NOIZEUS database. The VAD architecture is implemented on a Microcontroller-based system (MCU). Several tests have been conducted by performing real time acquisition via the Input/Output ports of the MCU-system.

Keywords: Voice Activity Detection, False Acceptance, Adaptive Thresholding, Non-Stationary Noise, Microcontroller Unit.

1. Introduction

The function of the Voice Activity Detection is to separate active voice from silence in utterances [1], it is an important component in many communication systems like mobile communications [2], speech coding [3], compression [4], digital hearing aids devices [5] and automatic speech recognition systems [6]. The G.729-B, normalized by the ITU-T in 1996 [7], is the most commonly VAD system. Later, the Adaptive Multi-Rate (AMR) speech coder was approved by the European Telecommunication Standards Institute (ETSI) for cellular mobile systems [8]. The VAD decisions of the ETSI-AMR are based on pitch and tone detection as well as correlated complex signal analysis [8]. The ETSI Advanced Front-End (AFE) coder has been adopted in 2002 for distributed speech recognition [9]. The VAD algorithm implemented in the ETSI-AFE uses Wiener filter and non-speech frame dropping to discard unvoiced intervals [9].

To enhance the robustness of VAD systems against strong noisy environments, various conventional statistical-based techniques were employed. Also, the widely used Gaussian plus Laplacian distribution is assumed to design noise-robust decision rules [10-14]. In [11], the Likelihood Ratio Test is used by assuming complex Laplacian and Gamma probability density functions (pdf) to model the DFT coefficients of the noisy speech. These methods act robustly when they are applied to relatively clean signals, while they exhibit poor performances in low Signal-to-Noise Ratio situations, or in presence of power noise transitions. To deal with these non-homogeneous situations, several speech enhancement techniques have been proposed, such as the Likelihood Ratio Sign Test (LRST), the Neyman–Pearson criterion [15] and the multiple observations Likelihood Ratio Test [16].

In this work, we propose a generalization of the VAD technique, presented in [14], for non-stationary noisy environments. Also, we introduce a VAD algorithm that maintains a constant False Acceptance probability within non speech periods. The iterative binary tests allow the rejection or the acceptance of the tested frame as active voice. The proposed speech detection is

based on the full-band energy as a decision variable. Ended, a moving window, containing energies of free-speech frames, is updated only in the case of null-hypothesis decision (absence of voice). By doing so, the above mentioned window, also called noise buffer, would likely contain the estimation of the background noise, even when the algorithm processes voiced periods. To initialize the noise buffer, we assume that the first 100 ms-frames of any call do not contain voiced signals [12].

To remove discontinuities that may appear in speech intervals, we also develop a smoothing procedure by taking into account the partial decisions related to the last contiguous frames.

The architecture of the proposed VAD is targeted on the STM32F746G-DISCO board [17] to build a real time system exploiting the integrated components such as Codec, Serial Audio Interface (SAI) and DMA channels. The obtained architecture has been evaluated via the acquisition of real speech signals and analyzed by the software tools available on the MCU-system.

2. Proposed VAD algorithm

A. Energy-based VAD

The diversity of both speech signals and background noise make the VAD problem quite complicated in practical situations. The VAD generates a voice activity decision every 10ms according to the specifications of the G.729 coder [7]. In general, four measures are required for VAD decisions; namely, full-band energy, low-band energy, zero-crossing and line spectral frequencies.

The full-band energy by frame, E_{FB} , corresponding to the logarithm of the normalized first autocorrelation coefficient is given by [7]

$$E_{FB} = 10 \cdot \log \left[\frac{1}{N} R_x(0) \right] \quad (1)$$

N is the frame size, $R_x(0)$ is the autocorrelation coefficient and x_j are the sampled speech plus noise amplitudes, thus

$$R_x(0) = \sum_{j=1}^N x_j^2 \quad (2)$$

We assume that speech and additive noise are described by Laplacian and Gaussian models respectively [6]. Also, under silence hypothesis (H_0), the AWGN samples are assumed Independent and Identically Distributed (IID) random variables. Consequently, the unvoiced samples are distributed according to the centered Gaussian probability density function (pdf) with the variance (σ^2) , also referred to as $G(0, \sigma^2)$.

In the rest of this study, we use $R_x(0)$ as a decision random variable instead of E_{FB} . In fact Eq.(1) refers to a monotonically increasing function, consequently E_{FB} and $R_x(0)$ are equivalents in term of binary decision. Thus, we define the decision variable for the k^{th} frame of length $2M$ samples as

$$E_k = \sum_{i=1}^{2M} x_i^2 \quad (3)$$

The IID processes $x_i \{i=1, \dots, 2M\}$ represent the AWGN samples within a silence frame. By defining y_i as the sum of two squared normal random variables ($y_i = x_{2i-1}^2 + x_{2i}^2$), we observe that y_i is governed by an exponential pdf of standard deviation σ , then

$$f_{y_i}(y) = \frac{1}{\sigma} \exp \left(-\frac{y}{\sigma} \right), \quad \{ i = 1, \dots, M \} \quad (4)$$

By substituting y_i in (3), E_k becomes the sum of M IID exponentially-distributed variables. Therefore, under H_0 -hypothesis, it is shown that E_k follows a Gamma distribution [18] of parameters (M, σ)

$$f_{E_k}(\varepsilon) = \frac{\varepsilon^{M-1} \exp(-\frac{\varepsilon}{\sigma})}{\Gamma(M) \sigma^M} \quad (5)$$

At iteration k , the k^{th} hypothesis test provides a binary decision to declare whether the frame under investigation is unvoiced (H_0) or contains noisy speech (H_1). To realize such a detection scheme, we define the False Acceptance rate F_A , as the probability to decide H_1 , whereas the frame under processing contains noise only (H_0), that is

$$F_A = Prob(E_k > Th/H_0) \quad (6)$$

Next, we compare the energy E_k of the k^{th} frame to the adaptive threshold Th and a partial decision d_k is made in favor of H_1 (voiced) or H_0 (unvoiced) in accordance to the following statistical test

$$E_k \geq_{H_0}^{H_1} Th \quad (7)$$

The adaptive threshold Th is closely related to the noise level, thus, the background level should be estimated by considering only the last frames having been declared unvoiced. Therefore, the adaptive threshold can be defined as a local mean level

$$Th = T \cdot Z \quad (8)$$

where $Z = \sum_{i=1}^{N_0} E_i$ is the estimated mean level of the background and E_i 's are energies of the H_0 -frames. The scaling factor T is set to keep a desired F_A probability during silence periods (H_0)

B. Constant false acceptance rate

To calculate T that guaranties a constant probability of False Acceptance, we should derive mathematical expression for the probability F_A . By substituting Th in (6) and using the pdf f_z and f_{E_k} of E_k and Z respectively, we obtain the probability F_A as

$$F_A = \int_0^\infty f_z(z) \int_{Th}^\infty f_{E_k}(e) de dz \quad (9)$$

Using the Moment Generating Functions (MGF) and the contour integral yields to [18]

$$F_A = -\sum_j \left(\text{Res}(\omega^{-1} \Phi_{E_k}(\omega) \Phi_Z(-T\omega) \right) |_{\omega=\omega_j} \quad (10)$$

$\text{Res}[\cdot]$ denotes the residue, Φ_Z and Φ_{E_k} are the MGF of Z and E_k under H_0 -hypothesis, respectively. ω_j are the poles of $\Phi_{E_k}(\omega)$ lying in the half left ω -plane.

As stated above, the variable $Z = \sum_{i=1}^{N_0} E_i$ is the sum of N_0 independent random variables E_i . In the other hand, each variable E_i is the sum of M independent random processes y_j , as shown in Eq.(3). Since y_j are IID, the MGF of their sum becomes the product of the individual MGF's [18], then

$$\Phi_{E_k}(\omega) = \prod_{i=1}^M \Phi_{y_i}(\omega) \quad \text{and} \quad \Phi_Z(\omega) = \prod_{i=1}^{MN_0} \Phi_{y_i}(\omega) \quad (11)$$

with

$$\Phi_{y_i}(\omega) = \int_0^\infty f_{y_i}(y) \cdot e^{-y\omega} dy \quad (12)$$

After the substitution of Eq.(4) into Eq.(12) and solving for the integral, the MGF's Φ_{E_k} and Φ_Z , given in (11), are derived to be respectively

$$\Phi_{E_k}(\omega) = \frac{1}{(1+\omega)^M} \quad \text{and} \quad \Phi_Z(\omega) = \frac{1}{(1+\omega)^{MN_0}} \quad (13)$$

where $2M$ is the frame size, and N_0 corresponds to the Noise-Buffer size according to the first unvoiced frames.

by substituting Eq.(13) into Eq.(10) and resolving the residue at the pole $\omega_0=-1$ of multiplicity order M , we get

$$F_A = \frac{-1}{\Gamma(M)} \left(\frac{1}{(-T)^{MN_0}} \right) \frac{d^{M-1}}{d\omega^{M-1}} \left\{ \omega^{-1} \left(\omega - \frac{1}{T} \right)^{-MN_0} \right\} \Big|_{\omega_0=-1} \quad (14)$$

with $\Gamma(M)=(M-1)!$

we let $U = \omega^{-1}$, $V = \left(\omega - \frac{1}{T} \right)^{-MN_0}$, and we use the fact that

$$\frac{d^L}{d\omega^L} (U \cdot V) = \sum_{i=0}^L \binom{L}{L-i} U^{(L-i)} V^{(i)} \quad (15)$$

where $U^{(L-i)}$ and $V^{(i)}$ are the $(L-i)^{\text{th}}$ and i^{th} derivative functions of U and V , respectively.

By using (15) into (14), we obtain after some algebraic manipulations the false acceptance rate to be

$$F_A = \sum_{i=0}^{M-1} \binom{MN_0-1+i}{MN_0-1} \frac{T^i}{(1+T)^{MN_0+i}} \quad (16)$$

We note that the factor T should be beforehand determined by solving numerically equation (16).

C. Proposed VAD Approach

The pre-computed factor T allows to keep a constant F_A probability against unvoiced regions. In turn, the partial decisions d_k are processed by the smoothing block in order to provide the final VAD binary decision. The smoothing principle consists of accepting an interval as speech if P successive frames, preceding the current one, have been declared H_1 i.e. ($d_{k-1}=1, d_{k-2}=1, \dots, d_{k-P}=1$).

Similarly, when a voiced period is processed, the algorithm decides H_0 only if the P previous frames are detected as noise. In fact, the above mentioned conditions have been added according to the stationary property of speech signals and then avoiding eventual discontinuities. Below, we present the necessary explanation about the working principle of our VAD system, as described by Figure 1.

The analog signal is sampled at 8 kHz, next the framing process (10 ms) leads to $2M=80$ samples by frame. The first N_0 incoming H_0 -frames (free speech) are loaded into a First-In First-Out (FIFO) noise buffer to set the initial background level ($Th=TZ$). Thereafter, at the k^{th} step ($k > N_0$), a partial decision d_k is provided by applying the test defined in (7) to decide if the k^{th} frame corresponds to speech plus noise (H_1) or noise only (H_0).

Next, the generated $(P+1)$ partial decisions (d_k) are stored into a shift register. Indeed, the P decisions preceding the current one (d_k), are continually checked to perform the smoothing if the above mentioned particular conditions are met.

- Smoothing

The role of this task is to remove undesirable discontinuities that may appear in both speech and non-speech regions, by generating smoothed final VAD decisions. However, we note that the smoothing task will introduce a slight latency of few tens milliseconds in the VAD output (Delay of P frames). Because of the low dynamic of the audio signal, the above delay cannot have any impact on the real time mode. Smoothing works by reversing few partial binary decisions already declared H_0 inside a voiced period (among P successive frames). Indeed, during a positive transition from H_0 to H_1 , at least P successive H_1 -frames should be detected to be classified as active voice ($VAD=1$). In a similar way, during a negative transition from H_1 to H_0 , the smoothed VAD is set to zero in the case where P successive H_0 -frames have been detected. The smoothing of d_k 's becomes effective only if the above mentioned conditions are met.

- Noise buffer updating

This procedure consists of inserting the most representative unvoiced energies. As shown in Figure.1, whenever $d_{k-P}=0$, the energy of the detected noise frame (E_{k-P}) is inserted into the FIFO Noise-Buffer. By doing so, the updated content of the buffer becomes available for the next hypothesis test.

- Scale factor adjustment

In the presence of uniform noise environment, where the power level is constant, the dynamic threshold $Th = TZ$ guaranties a constant F_A via the pre-computed value of T (see Eq.16). However, in non-homogeneous situations caused by abrupt power noise transitions during the same session call, the proposed VAD exhibits intolerable false acceptance rate leading to poor detection performances. To circumvent this problem, the factor T is automatically corrected whenever a transition region is under processing. A long-term set of energies is stored in a FIFO Buffer over the f_u frames preceding the one under processing (Figure.1.b). We assume that E_{max} and E_{min} represent extreme values of the FIFO register of size f_u . For every set of f_u frames, the moving energy difference ($E_{max} - E_{min}$) is compared to a predefined energy deviation threshold Δ_E , to decide if an abrupt power transition has been occurred. Typically, a full-band energy deviation

above 15 dB indicates a significant change in the background noise environment [7]. Consequently, the scaling factor adjustment takes place according to the following condition

$$E_{max} - E_{min} \geq \Delta_E \quad (17)$$

Figure 1. Block Diagram

Noting that the condition (17) should be tested, every f_u frames, in order to reset the adaptive threshold TZ within the interval $[E_{min}, E_{max}]$ whenever a significant environment change is detected; in this case, the factor T is updated as follow

$$T = \frac{E_{min} + \alpha \cdot \Delta E}{Z} \quad (18)$$

where α corresponds to the adjustment level parameter which has been empirically fixed through intensive simulation, using Noizeus Database [20].

3. Real time implementation

The proposed VAD method is implemented on the high performance MCU ARM Cortex®-M7 STM32F746NG board [17], which provides a single floating point unit supporting all ARM® single precision instructions and data types.

Figure.2 illustrates the function of the real time system. It consists of three fundamental parts; an audio source (from the microphone), a MCU board and the speaker. The analog speech signal from audio source is passed through the Analog to Digital (A/D) converter of the codec WM8994ECS/R to be sampled at 8 kHz with a 16 bits linear PCM (Pulse Code Modulation) data. The obtained digital signal will be frame-by-frame processed via the proposed real time VAD application. Finally, the output digital data is converted to an analog signal through the D/A converter and passed through the speaker, which allows a subjective evaluation of the studied VAD method.

A. Design of hardware implementation

The hardware implementation architecture is described in Figure.2, audio streaming data is digitized by A/D of the integrated codec WM8994ECS/R, the two blocks A and B are chosen to transfer obtained samples from Serial Audio Interface (SAI) to Direct Memory Access (DMA). The Code is developed using C language, compiled and loaded to the MCU board via USB port using embedded IDE of STM software.

Figure 2. Real time system architecture on MCU board

B. Data and memory mapping

The efficiency of a real time microcontroller-based application, in terms of area and power consumption depends, among others criterions, on the memory requirements of the implemented architecture. In the following, we first describe the memory mapping required to store and to process the incoming audio frames. We also present an overview of the main variables and constants used by the proposed VAD algorithm. Table 1 summarizes the signification, the size, the type and the address locations of the used memory resources.

The used sampling frequency is 8 KHz with Stereo mode, therefore each 10 ms we get one recorded data frame. Each frame is composed by two half blocks fulfilled and structured as detailed in Figure. 3. Thus, 320 bytes should be online stored for the two audio input channels (right and left), however, we processed only 160 bytes corresponding to a single channel, and ignore the second data channel.

Table 1. Data organization.

Variable name	Designation	Type	Number of bytes	Starting Address
T	Scaling factor	Float	4	0x20000114
P	At least P accepted voiced frames	unsigned short int	2	0x20000076
Δ_E	Energy Variation threshold	Float	4	0x20000118
A	Adjustment level	Float	4	0x2000011c
Cf	Counter Frame	unsigned long int	4	0x20000120
frm_prsnt	Buffer containing samples of the current frame	Float	4*80	0x20000124
Rx	Autocorrelation coefficient	Float	4	0x20000264
Ef	Energy Full Band	Float	4	0x20000268
Z	mean level estimation of the background energy	Float	4*10	0x2000007c
VAD_buff	Partial Decisions Register	unsigned short int	2*(P+1)	0x200000cc
Ef_buff	FIFO Energy-Buffer of the last (P+1) frames	Float	4*4	0x200000dc
E _{mm}	FIFO Energy-Buffer of the last fframes	Float	4*15	0x200000a4
E _{min}	Energy Min	Float	4	0x20000104
E _{max}	Energy Max	Float	4	0x20000100
Th	Adaptive Threshold	Float	4	0x20000270
Vf	Final VAD decision	unsigned short int	2	0x20000074

Figure 3. Memory mapping for a stereo audio frame

4. Experimentation and results

For evaluation purpose, we compared our approach to the VAD of the standard G.729 through the well-known NOIZEUS Database [20]. To simulate non-stationary noisy situations, we generated power-controlled synthetic AWGN to be added to the NOIZEUS clear utterances. In addition to that, several real time tests were applied via online audio acquisition, by exploiting the MCU sound devices.

A. NOIZEUS database

The NOIZEUS database [20] consists of thirty clear utterances, corrupted by different real world noises taken from AURORA database [21], namely: restaurant, car, street, airport, babble, exhibition hall and train station, at different SNR levels 0 dB, 5 dB, 10 dB, 15 dB, all files are saved in wav format with 8 KHz sampling and 16 bit PCM coding.

To evaluate our system comparatively to the G.729 VAD, we have taken into account the usual criteria [10];

- Correct: Correct decisions for both voiced and noised frames.
- TR (True Rejection rate): obtained by combining the front end clipping (FEC) and the mid speech clipping (MSC) indicators.
- FA_{ex} (False Acceptance rate): obtained by combining carry over (Over) and noise detected as speech (NDS) indicators.

Table 2 summarizes the results for the whole database, by using the following values; T=0.13, P=3, N₀=8 and a prescribed False Acceptance value of 0.06×10^{-3} .

Both the proposed VAD and the G.729 have been applied to the whole NOIZEUS database. The obtained results using above criteria are summarized in Table 2. We notice that the proposed VAD acts robustly, particularly in presence of high noise power (0dB and 5 dB). Indeed, a high value of the Correct parameter shows a satisfactory detection performance, while a low FA indicates a good compression rate. However, in usual moderate noisy environments, we note that the suggested VAD and the G.729-B exhibit almost the same performances. Let us recall that the criterions Correct, TR and FA are just necessary to validate the mathematical derivation (section 2.A), and then, to show the behavior of the proposed system against several operational situations. To be completely accurate, the comparison with the G.729-B should take into account others

important criterions such as the bandwidth consumption, where the G729 is known to be a reference in this area.

Table 2. Comparison with G.729-B VAD using NOIZEUS database

SNR (dB)	Approach	Correct	TR	FA _{ex}	FEC	MSC	OVER	NDS
15	G.729	80.440	5.701	13.861	1.020	4.691	1.221	12.640
	Suggested	85.062	2.730	12.202	0.601	2.130	1.600	10.602
10	G.729	79.540	4.460	16.003	0.760	3.702	1.491	14.510
	Suggested	83.704	3.811	12.491	0.730	3.081	1.603	10.881
5	G.729	78.931	3.692	17.380	0.512	3.180	1.670	15.712
	Suggested	82.801	4.731	12.460	0.780	3.950	1.582	10.880
0	G.729	78.060	4.005	17.942	0.442	3.571	1.721	16.221
	Suggested	80.922	6.110	12.961	0.810	5.302	1.600	11.363
Mean	G.729	79.240	4.461	16.300	0.680	3.780	1.530	14.770
	Suggested	83.121	4.350	12.530	0.731	3.621	1.600	10.931

B. Non-stationary noisy situations

The proposed VAD-system is evaluated in non-stationary background by concatenating four clear audio signals from NOIZEUS to form a clear wav file of 10 seconds, this file is corrupted by synthetic white noise with different SNR (-5dB, 10dB, 25dB, 10dB, -5dB), each SNR level is applied during 2 seconds. In these experimental tests, it is essential to consider several situations ranging from weak to strong noisy environments. Low SNR intervals (-5 dB, 10 dB) have been generated with intending to focalize on the behavior of the proposed VAD system against highly noisy backgrounds. Such extreme situations may be encountered when a phone call occurs in usually noisy places (airports, train stations, street ...). Others factors which are intrinsic to the communication system can also lead to an intolerable noise level along with a poor call quality. For instance, IP-packets can suffer from RF disruptions and attenuations during the instant they are transmitted via wireless LAN networks, leading to strong noisy situations in VoIP communications.

Figure 4a and 4b depict the VAD decisions for G.729 and our suggested algorithm respectively. The obtained results are presented in Table 3.

Table 3. Proposed system Vs G.729-B in non-stationary situation

VAD Method	Correct	TR	FA	FEC	MSC	Over	NDS
G.729-B	75.32	13.10	11.63	1.31	11.82	2.70	8.91
Proposed system	84.61	5.72	9.70	1.72	4,02	2.51	7.20

a. G.729-B

b. Proposed system

Figure 4. Voice Activity decisions for inhomogeneous environments

As summarized in table 3, the G.729-B method exhibits an intolerable increase of the critical parameter True Rejection TR (13.1%) and a relatively high value of the False Acceptance (11.6%), which causes a decrease of the Correct parameter (75.3%). In the other hand, we note a consequent improvement of the Correct parameter for our VAD algorithm (84.6%), which clearly lead to low values for both parameters TR (5.7%) and FA(9.7%). Through the obtained results, it clearly appears that the proposed detection scheme outperforms the G.729-B in terms of Correct decisions rate, true rejection and false acceptance rate, in particular in non-stationary situations.

C. Real time tests

In order to evaluate the online behavior of the proposed method using the MCU board, experimental audio signals embedded in real-world noisy environments (babble crowd of students) have been recorded. The curves presented in Figure.5 have been displayed in real time while recording the signal via the STM-STUDIO tool [22]. The first curve shows the full-band energy versus the adaptive threshold. We observe that the VAD is set to 1 whenever the full band energy exceeds the adaptive threshold, which corresponds to a voiced frame. Noting that the VAD outputs are illustrated in red on the third curve, while the second curve shows the recorded signal.

As mentioned before, we only keep frames declared as speech and set unvoiced frames to 0, in order to get a subjective evaluation and to guarantee that the signal has not been degraded after the VAD processing.

Figure 5. Real-time monitoring for a recorded signal.

D. Real time execution

The suggested VAD algorithm is implemented and tested on the MCU board in order to validate its real time operation mode. To this end, several tests have been executed using a sampling frequency of 8 KHz. After acquisition of the last sample from each frame (S_{80} , S_{160} , S_{240} ...), as shown in Figure.6, the full data frame are passed to our VAD algorithm to provide the final decision. By placing break points in our implemented code program, the average cycle counter has been estimated to be 200 clock cycles. With a CPU clock of 49.142 MHz, the processing time has been determined to be $4\mu s$, which is sufficient regarding to the sampling frequency used in speech processing ($125\mu s$ at 8kHz or $62,5\mu s$ at 16 kHz).

Figure 6. Real-time VAD-Timing

5. Conclusion

Through this article, we propose a low complexity VAD approach, using adaptive thresholding to detect voiced periods in presence of non-stationary noise. The attractive property of the considered Voice Activity Detection scheme is its aptitude to keep a prescribed false acceptance rate against silence periods. An exact expression of the probability of false acceptance (F_A) has been derived in order to set the scaling factor value, and then to control the F_A rate. However, the presence of abrupt noise transitions in non-stationary noisy situation leads to an intolerable false acceptance rate (F_A) of the proposed system. To deal with this problem, the scale factor should be adjusted whenever some particular conditions are met. Also, to avoid undesirable discontinuities in both speech and silence intervals, a smoothing procedure has been carried out by analyzing contiguous binary decisions preceding the frame being processed. Using NOIZEUS data base, synthetic audio signals have been generated to show the VAD performances under different noise conditions in non-homogeneous situations.

The results show that the proposed VAD acts robustly against non-homogeneous noisy environments, where different SNR situations have been simulated within the same call period. By considering usual criterions, namely; TR, Correct, and F_A measures. The proposed VAD and the G.729-B perform similarly in moderate environments. However, we note that the proposed system slightly outperforms the normalized G.729-B algorithm in highly noisy backgrounds.

Finally, several real time tests have been carried out by implementing the VAD-Algorithm. The architecture is targeted on the MCU-board STM32F746NG. The behavior analysis has been done through online audio acquisition via the I/O ports available on the target board. Online operations show a reduced computational complexity, along with an overall latency of 4 μ s. Computational requirements seem to be widely sufficient up to 16 kHz sampling.

6. References

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