Advancements in gunshot signal detection using acoustic sensors

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ABSTRACT: The detection of impulsive acoustic signals and their classification as gunshots plays a crucial role in systems designed to pinpoint the origin of gunshots fired by snipers or regular shooters. With significant applications in the military context, gunshot detection systems face substantial challenges related to their use in operational environments, which often involve multipath propagation and environmental noise. Moreover, these systems need to be capable of real-time operation. This article addresses modern methods for detecting and classifying the acoustic components of gunshot signals, proposing modifications to enhance their performance and evaluating them using a diverse dataset of real-life gunshot signals. The results are compared to determine the most suitable method for hardware implementation. The text provides valuable insights for developing gunshot detection systems in challenging environments.

KEYWORDS: *Gunshot Signals. Sniper. Detection. Classification. Direction of Arrival.*

RESUMO: A detecção de sinais acústicos impulsivos e sua classificação como disparos de arma de fogo desempenham um papel crucial em sistemas destinados a localizar a origem de tiros por caçadores ou atiradores em geral. Com aplicações de relevância no contexto militar, os sistemas de detecção de tiros enfrentam desafios substanciais relacionados ao seu uso em ambientes operacionais, que frequentemente envolvem propagação multipercurso e ruído ambiental. Além disso, esses sistemas precisam ser capazes de operar em tempo real. Este artigo aborda métodos modernos para a detecção e classificação das componentes acústicas dos sinais de tiro, propondo modificações visando aprimorar seus desempenhos e avaliando-os com uma diversificada base de sinais de tiros reais. Os resultados obtidos são comparados para determinar o método que se mostra mais adequado para uma implementação em hardware. O texto fornece insights valiosos para o desenvolvimento de sistemas de detecção de tiros em ambientes desafiadores.

PALAVRAS-CHAVE: *Sinais de Tiro. Caçador. Detecção. Classificação. Direção de Chegada.*

1. INTRODUCTION

Contemporary conflicts are intrinsically related to the application of technology on the battlefield. The Ukraine War exemplifies military applications that encompass missiles, drones, radars, and cyberwarfare [1]. Still, conventional military assets ubiquitously and lethally persist in security force ranks. This study highlights a notoriously silent threat: snipers [2].

Snipers have the mission of penetrating enemy defenses by refined camouflage techniques, eliminating strategic targets, and causing confusion in enemy troops [2]. Snipers carry a mystical aura the media has highlighted, including as in movies such as *Pacific Rim* (2001, which tells the story of a Soviet soldier named Vasily Zaitsev at the Battle of Stalingrad) [3] and *American sniper* (2014, based on the autobiography of Chris Kyle, an American sniper who achieved notorious feats in the Iraq War) [4]. Other notable examples include Finnish Simon Häyhä (known as "White Death") and Lyudmila Pavlichenko (known as "Lady Death"), born in the Kiev Province (then Russian Empire) [5].

The main tactics against sniper action consist of moving the troops out of the enemy's angle of sight and shooting at them in to force them to change positions [2]. However, these actions require knowledge of the original direction of the shot [6]. Thus, research carried out more than a decade ago at the Military Institute of Engineering Digital Signal Processing Laboratory [7-13] stands out as it aimed to improve the algorithms to estimate enemy snipers' direction of arrival. This takes place by processing the acoustic components of a firing signal: the shock wave (SW) in the case of a supersonic projectile and the explosion of the propellant charge muzzle blast (MB).

Armies around the world apply the available commercial solutions to obtain this direction. Examples

include the American Boomerang III (Raytheon), the Turkish TRV-SD 500 (Transvaro), and the French Pillar V (Metravib Defence) systems [14-16].

The estimation of the direction in which snipers fired their shots requires the previous detection of their shots, which comprises two steps: detecting impulsive signals and classifying them into SW or MB, when applicable [6]. This study aims to evaluate the performance of gunshot signal detection algorithms, propose adaptations to improve their results, and indicate the best option for practical applications. It analyzed four methods: cross-correlation [7], energy spectral analysis [17], signal-to-noise ratio (SNR) [18], and neural networks [19].

Once an impulsive signal is detected, it is necessary to determine whether it comes from a firing signal (classify it as SW or MB) or not. SW constitute acoustic waves generated by the Mach effect in the trajectory of the supersonic projectiles from a rifle, for example [20]. On the other hand, MB corresponds to the acoustic wave formed by the difference in pressure between the external environment of the weapon and the gas within the weapon that undergoes heating by projectile charge activation [20]. A relevant piece of information about SW is that it has an "N" shape and a duration from 0.3 to 0.5 ms, whereas MB lasts from 3 to 5 ms [20].

2. FUNDAMENTAL CONCEPTS

2.1 Geometry of the problem

The typical geometry of detecting sniper shots consists of three elements: shooter, target, and microphone array. An array of microphones is used to estimate the direction of arrival. Figure 1 shows the arrangement of these elements and indicates the SW and MB wavefronts generated by the trigger.

The typical configuration of a shot may differ from Figure 1 due to the absence of either SW or MB, which occur when objects or barriers prevent acoustic waves from reaching the microphone array [6]. The SW component may also be absent if the microphones are positioned behind the shooter and thus out of the shockwave field of view.

Figure 1 - Typical geometry of the detection problem of a supersonic projectile.
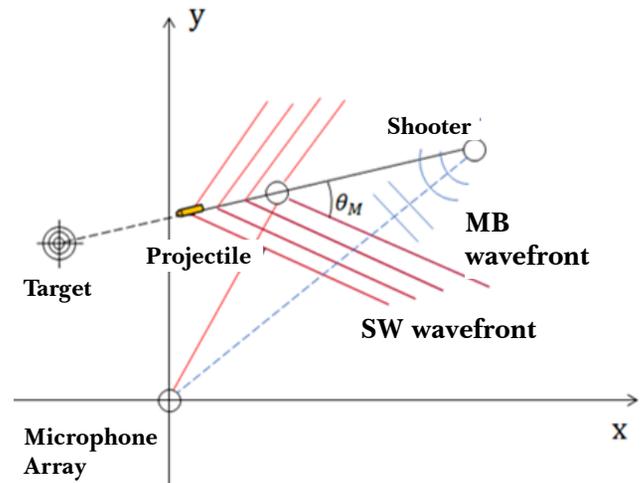
2.2 Impulsive Signal Detection

The first stage of the processing addressed in this study consists of verifying whether the time window of the analyzed acoustic signal corresponds to an impulsive signal. Detection involves ascertaining whether a specific parameter obtained by applying an algorithm (e.g., the peak cross-correlation of the acquired signal window with a known SW model) exceeds a certain threshold. Training occurs by varying the threshold in a range of values, forming a receiver operating characteristic (ROC) [21].

This curve is constructed from the following performance measures: true (TPR) and false positive rates (FPR). TPR and FPR, expressed by Equations (1) and (2) [21], respectively, are best understood by a confusion matrix, as in Table 1.

$$TPR = \frac{TP}{TP + FN} \qquad (1)$$

$$FPR = \frac{FP}{FP + TN} \qquad (2)$$

In the ROC curve for the FPR × TPR axis system, the closer the curve gets to the point (FPR, TPR) = (0.1), the better the detector performance. Since in practice this point is usually unable to be obtained,

the point of operation is chosen based on operational criteria.

Table 1 - Confusion matrix

		Truth Condition	
		Present	**Absent**
Test Result	Positive	TP	FP
	Negative	FN	TN

2.3 Classification of Shooting Signals

The classification of an impulsive signal involves deciding which components emerge in an audio window, whether they are SW, MB, or NS (non-shooting window, i.e., the impulsive signal fails to characterize a shot). This typification requires extracting parameters from the signal and applying a classification criterion to these parameters. This study used the following four features: the peak of cross-correlation with a model, the linear predictive coding (LPC) and Mel-frequency cepstral coefficients (MFCC), and the normalized signal energy [7] [17] [18] [19].

Table 2 - Feature vector

Features	Indices
Cross-correlation with the SW/MB AGLC Model	1 and 2
Cross- correlation with the SW/MB FAL Model	3 and 4
Cross- correlation with the SW/MB M2 Browning Model	5 and 6
Cross-Correlation with IA2 SW/MB Model	7 and 8
LPC coefficients (20)	9 to 28
MFCC coefficients (26)	29 to 54
Normalized signal power (Z)	55

Table 2 shows the distribution of the classification features. The weapons are detailed in Section 3.1. Each method extracts a number of parameters. Processing (detection and classification) was performed on Matlab® Classification Learner or Neural Pattern Recognition, in which the input of both consists of an array with the features of a set of windows and the output is a function that performs the sorting.

3. METHODOLOGY

The detection and classification of impulsive signals, such as SW or MB, involve several initial steps, from acquiring audio signals to training algorithms to automatically achieve the goals of this study. Next, we describe the used weapons, the composition of the signal dataset for training and testing, its preparation before the application of the algorithms, and the analyzed methods, highlighting details of the original algorithms and the implemented adaptations.

3.1 Signal dataset and weapons

The AGLC, the FAL, the IA2, and the M2 Browning [22–25] are weapons used by Brazilian Army snipers (which constituted the signal dataset), all of which can perform supersonic firing. Some technical characteristics of each of these weapons are shown in Table 3.

Signals were sampled by a ECM8000 Behringer [26], used in previous arrangements to acquire audio from the main dataset in this study.

A 96-kHz sampling frequency was used to process the audio signals. Signals that had initially been acquired at 44.1 kHz were resampled on Matlab®.

The signals were collected from four shooting ranges: Centro de Avaliação do Exército (CAEx) 2011, Centro de Instrução de Operações Especiais (CIOpEsp) 2010, CAEx 2014, and Centro de Instrução Almirante Milcíades Portela Alves (CIAMPA) 2010. Table 4 shows the distribution of shooting signals for training.

Table 3 - Characteristics of some weapons used by Brazilian snipers

Weapon	AGLC	IA2	FAL	M2 Browning
Caliber	.308" or 7.62 mm	7.62 mm	5.56 mm	.50" or 12.7mm
Initial velocity (m/s)	820	840	780	930
Range (m)	800	1800	300	300
Manufacturer	IMBEL	IMBEL	IMBEL	General Dynamics

Table 4 - Distribution of SW and MB during training for each base

Dataset	Weapon (distances)	Number of Signals
CAEx 2011	AGLC (300 to 700 m)	28 SW and 28 MB
	FAL (300 to 500 m)	20 SW and 20 MB
	IA2 (300 to 500 m)	21 SW and 21 MB
	.50 BMG (300 to 500 m)	16 SW and 15 MB
CIOpEsp	AGLC (200 m)	5 SW and 5 MB
	PSG1 (200 m)	3 SW and 3 MB
CAEx 2014	AGLC (540 to 1062 m)	43 SW and 43 MB
CIAMPA 2010	FAL (31 to 74 m)	23 SW and 10 MB

All signals were divided into 20-ms windows and a 50% superposition to obtain windows containing SW, MB, or NS. The distribution of these windows for training and testing is shown in Table 5. In training, a number of SW, MB, and NS windows were separated to avoid classification bias and maintain balanced quantities. In testing, 60 complete audios of the shooting dataset were used (12 from CAEx 2014, 40 from CAEx 2011, five from CIOpEsp 2010, and nine from CIAMPA 2010), simulating the large intervals of time in which snipers will fire no shots in the battlefield. This resulted in a discrepant number of NS windows relative to the other classes.

Table 5 - Window Distribution

Window Type	Training	Test
SW	159	60
MB	144	60
NS	313	36476

Previously described shot signals [27] available for download on the internet were used to evaluate the performance of the most efficient method to process the signals available at the Military Institute of Engineering Digital Signal Processing Laboratory

in comparison to another dataset. At this second base, three different weapons were used: .45-," .40-," and 9-mm automatic pistols with 12 shots in nine positions, totaling 324 shots [27]. The projectiles of these pistols are not supersonic, so the recorded audio only features MB.

3.2 Preparation of the dataset

As the acquisition of the firing signals occurred under several environments and microphone gain values, the energy of each signal was normalized after the DC level was removed (if present). To reduce the influence of noise (especially on the MB components of the signals, which, have the lowest SNRs due to shooters' further distances), a median filter [9] was

applied to enhance the impulsive portions of the audio signals.

3.2 Methods

The four methods in this study will be detailed below. Training for each method involves two steps: a detection threshold (e.g., obtained by constructing a ROC curve and choosing an operating point) and generating a criterion or function (e.g., by a machine learning algorithm) that classifies windows into SW, MB, or NS. Both steps are shown in Figure 2. The testing of each method involves a detection threshold and a classification criterion obtained in training with audio signals divided into windows containing shots (SW, MB, or both) or no shots (only ambient noise).

**Figure 2 -** General flowchart of detection and classification.
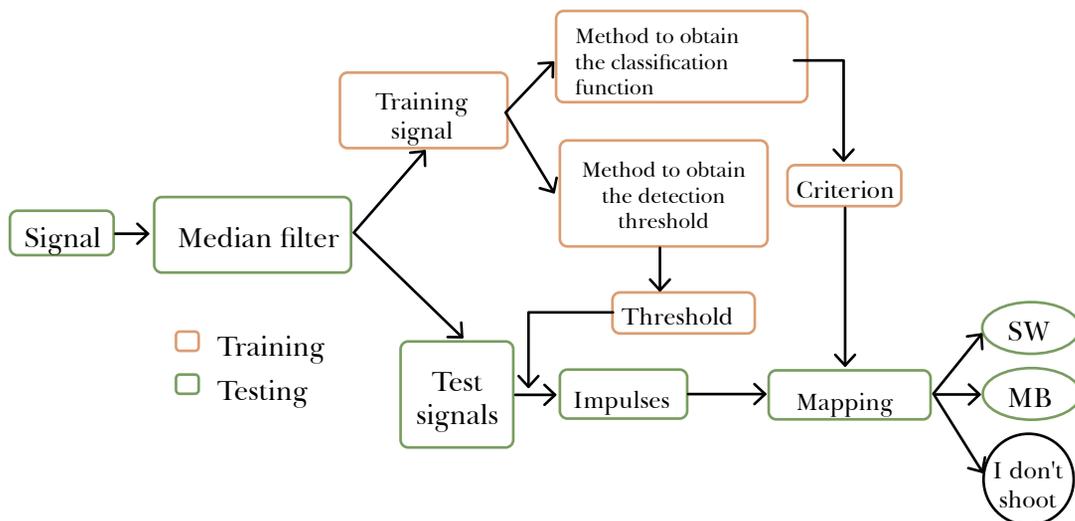
3.2.1 Cross-Correlation Method

In the original version of this method, detection is performed by applying the generalized cross-correlation algorithm to each window, indicating an impulsive signal if the value from the cross-correlation peak exceeds a threshold. In detection training, as in Figure 3, the cross-correlation of each training signal

window with an AGLC SW model (reference signal) is computed. The cross-correlation peaks are separated and converted into a confusion matrix. Obtaining several confusion matrices by varying the threshold generates an ROC curve that enables the choice of the operating point. In our experiments, the operating point chosen was TPR > 90%.

Figure 3 - Delimitation of the detection threshold in the Cross-Correlation Method.
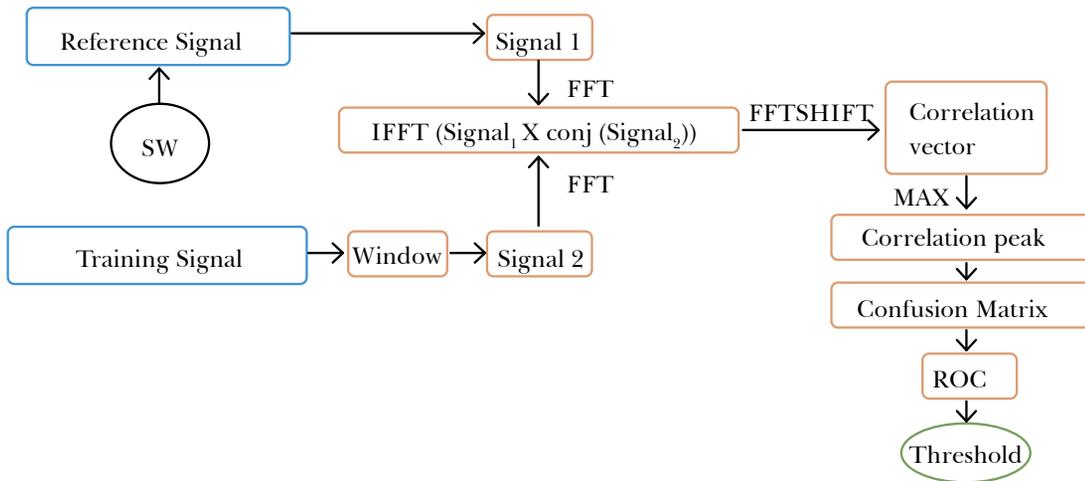
Source: [7]

The method in [7] exclusively uses the SW of the AGLC rifle as a reference signal and includes no algorithm to distinguish SW, MB, and NS. The SW and MB components of the four weapons in Table 3 were used in this study, i.e., the first eight parameters (cross-correlation peaks) of the trait vector in Table 2. The modified version of this method uses the non-linear function on Matlab® Classification Learner as a classification algorithm according to support vector machine kernel (SVM Kernel).

3.2.2 Energy spectral analysis

Obtaining the detection threshold of this method involves computing the energy E_{win} from the short-time Fourier transform of the $x(n)$ windowed signal, i.e., $X(k)$ corresponds to the DFT matrix of the product $x(n)$ by a window $w(n)$, in which "n" is the discreet time and "k" is the index (the *bin* frequency) of the DFT. E_{win} obtains the impulsive signal detection function for each D_{win} window, according to Equations (3) and (4) [17]. If D_{win} exceeds the threshold, it is assumed that the window sign is impulsive [17]. To obtain this threshold, a ROC curve was constructed to enable the choice of the operating point (in our experiments: TPR > 90%).

$$E_{win} = \sum_k |X(k)|^2 \qquad (3)$$

$$D_{win} = \frac{E_{(win+1)} - E_{(win-1)}}{3} \qquad (4)$$

This method dispenses with classification training as it is simply based on the two conditions described by Equations (5) and (6) [17].

$$S1: E_{(f>1600Hz)} > 2E_{(f<1600Hz)} \qquad (5)$$

$$S2: Impulse(i) - Impulse(i-1) > 0.2 \qquad (6)$$

Table 6 indicates how the classification in this method occurs according to conditions S1 and S2 [17].

Table 6 - Classification by the Energy Spectral Analysis Method

		S1	
		True	False
S2	True	SW	NT
	False	NT	MB

3.2.3 SNR Analysis

In this method, the detection threshold is obtained by the normalized energy of the signal (Z) [18]. If the Z value of a window exceeds the threshold, it contains an impulsive signal. Let $x(n) = hs(n) + r(n)$, in which $r(n)$ is noise (considered Gaussian white), $s(n)$ is the impulsive sign in case of $h = 1$ (the presence of an impulsive signal). If $h = 0$, that window showes

no impulsive signal [17]. Thus, the signal energy of the window normalized by the noise energy in that window (parameter Z) is given by Equation (7) [18].

$$Z = \frac{1}{\hat{\sigma}_r^2} \sum_{n \in Window} x^2(n), \quad (7)$$

in which $\hat{\sigma}_r^2 = \sum_{n \in Window} r^2(n)$ is an estimate of the energy of the noise.

Detection training in this method begins by obtaining the parameter $a = WT$, in which W is the bandwidth of SW or MB signals and T is the sampling period. Next, the lowest SNR value of the SW and MB windows is determined. With a, it is used to compute P_m (probability of missing an impulsive signal) and P_{fa} (probability of indicating that a window without impulse is impulsive), according to Equations (8) and (9), in which Γ is the Gamma function, γ is the lower incomplete Gamma function, Q_a is the Generalized Marcum Q function, and λ it is the decision-maker [18].

$$P_{fa} = FP = 1 - \frac{\Gamma(a, \frac{\lambda}{2})}{\Gamma(a)} \quad (8)$$

$$P_m = FN = 1 - Q_a(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (9)$$

Next, the odds charts of P_{fa} and P_m due to λ are obtained. The graph of P_m is a growing function with the increase of λ, whereas the graph of P_{fa} is a decre-

asing function [18]. The operating point chosen for this study was $P_{fa} < 2\%$.

To train the classification, 18 parameters (eight cross-correlation peaks and 10 LPC coefficients) were used as input on Matlab® Classification Learner. The function generated by the SVM Kernel was chosen as a classification criterion due to its better performance for this method.

3.2.4 Classification Using Neural Networks

Originally, this method failed to clearly distinguish detection from classification. To improve it, we chose to incorporate the detection mechanism in the SNR method [18]. Matlab® Neural Pattern Recognition was used to train the classification. Input considered a 55-element vector composed of eight cross-correlation peaks, 20 LPC coefficients, 26 MFCC coefficients, and 1 Z parameter. The output of this application was modeled by a function simulating a two-layer feed-forward neural network: a hidden layer with 10 neurons (sigmoid activation function) and a a three-neuron exit layer (softmax activation function). Scaled conjugate gradient was used as the algorithm for training. The neural network architecture of this method is shown in Figure 4.

Figure 4 - Feed-forward network structure used in by the Neural Network Method.
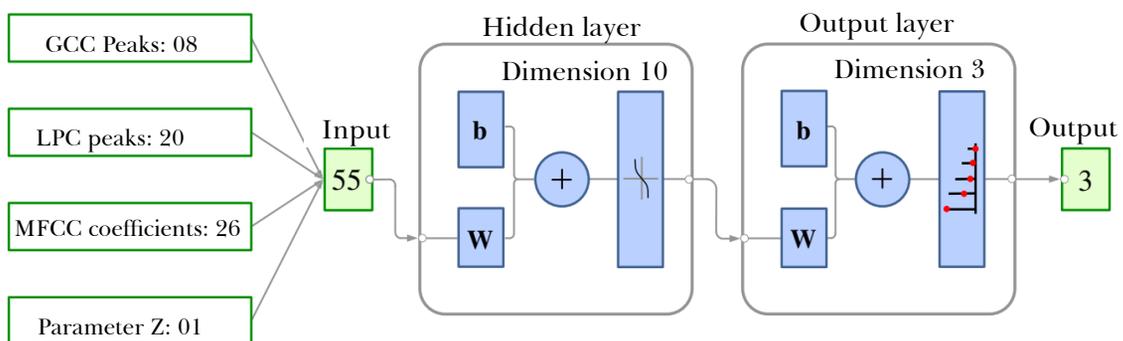
4. EXPERIMENTAL RESULTS

Table 7 shows the analysis of the training results, highlighting the TPR and FPR metrics for each method in the detection and classification stages.

Table 8 shows the runtimes. This research conducted all processing, including training and testing, on

Matlab® using a computer equipped with an Intel® Core™ i5-8250U processor with a CPU @1.60GHz 1.80GHz and 8GB RAM with no SSD.

Energy spectral analysis showed the shortest runtime in windows with pulses as its classification algorithm dispenses with obtaining new parameters. Neural networks obtained the second-best runtime

despite its greater number of parameters. This result stems from the robustness of the classification algorithm of this method, which is simpler than the SVM Kernel approach, a nonlinear technique.

Table 7 - Training Result

Method	TPR	FPR
Cross-Correlation	93.79 %	6.21 %
Energy Spectral Analysis	90.03 %	4.70 %
SNR	97.27 %	5.25 %
Neural Networks	95.83 %	2.28 %

Tabela 8 - Runtime

Method	Window without impulse	Window with impulse
Cross-Correlation	2.26 ms	6.49 ms
Energy Spectral Analysis	3.65 ms	3.82 ms
SNR	1.13 ms	11.72 ms
Neural Networks	1.02 ms	4.80 ms

Table 9 shows the test results. Cross-correlation detected all SWs but with a relatively lower detection of MBs than the other methods. The neural network detected and classified the largest number of MBs.

Table 9 - Gross Results (correct windows)

Method	SW (60)	MB (60)	NS (36476)
Cross-Correlation	60	17	36471
Energy Spectral Analysis	56	31	36461
SNR	53	48	36471
Neural Networks	55	54	36457

Table 10 shows the classification errors during the test. It shows that SNR and neural network analysis had fewer total errors than the other methods.

Table 10 - Gross errors (wrong windows)

	Cross-Correlation (48)	Energy Spectral Analysis (67)	SNR (19)	Neural Networks (30)
SW → MB	0	1	7	5
SW → NS	0	2	0	0
MB → SW	0	3	2	1
MB → NS	43	26	10	5
NS → SW	0	1	1	4
NS → MB	5	34	4	15

Table 11 shows the results of a suggested authorial coefficient, as per Equation (10), that prioritizes MB TPR over the SW TPR. This choice is justified by the sniper's direction estimation algorithm using MB information as its input data. In this perspective, neural networks obtained the best result.

$$Coefficient \ = \ \frac{3TPR_{SW} + 5TPR_{MB}}{8} \qquad (10)$$

Table 11 - Coefficient Equation (10)

Method	TPR_{SW}	TPR_{MB}	Coefficient
Cross-Correlation	1	0.283	0.552
Energy Spectral Analysis	1	0.516	0.697
SNR	0.933	0.8	0.849
Neural Networks	0.916	0.9	0.906

Table 12 shows the results by error rate coefficient, given by Equation (11) [21], in which N = 36596 (the total number of windows), in which SNR performed better in the face of errors.

$$Error \ Rate \ = \ \frac{FN + FP}{N} \qquad (11)$$

Table 12 - Error rate

Method	FN	FP	Error Rate
Cross-Correlation	43	5	0.13 %
Energy Spectral Analysis	25	35	0.16 %
SNR	17	5	0.06 %
Neural Networks	11	19	0.08 %

Table 13 shows the results of each algorithm in the application of the F1 score coefficient, as per Equation (12). This coefficient is important in analyzing data sets with large discrepancies in the number of samples between classes [21], as in the test signals.

$$F1 = \frac{2TP}{2TP + FP + FN} \tag{12}$$

Table 13 - F1 Score Coefficient

Method	TP	FN	FP	F1 (%)
Cross-Correlation	36818	43	5	99.9348
Energy Spectral Analysis	36806	25	35	99.9185
SNR	36844	17	5	9.9701
Neural Networks	36836	11	19	99.9592

These results suggested neural networks as the most appropriate method to detect and classify firing signals. It classified MB well and showed a low computational complexity as it training took place offline.

Table 14 shows the results from applying neural networks (considered the most appropriate for the application in the dataset in [27]). In this context, the rural situation refers to the shooting signals from the datasets in this study (rural environment), whereas the urban setting refers to the shooting dataset in [27]. Even when used in a set of firearms unlike those in training, highlighting the absence of supersonic characteristics in the projectiles and a high degree of multipath typical of urban environments, the method could separate the MB, achieving a TPR higher than 70% for all weapons in [27].

Table 14 - Test results at the urban dataset [27] with training at the rural dataset

	Caliber.45	Caliber.40	Caliber 9 mm
MB→MB	80	79	92
MB→NS	28	29	16
NS→MB	4	5	17
TPR	74.07%	73.15%	85.18%

Table 15 shows the results of the training and testing under several training/test configurations.

Table 15 - Test results with different types of training and test scenarios

Training	Test	TPR
Rural	Rural	95.83 %
	Urban	77.47 %
Urban	Rural	90.56 %
	Urban	88.88 %
Mixed	Rural	90.56 %
	Urban	85.18 %

5. Conclusion

This research [28] aimed to replicate and compare algorithms to detect and classify impulsive signals into three categories: SW, MB, or NS. For this, it developed routines on Matlab® to train and test each of the four chosen methods. To improve classification results, it suggested modifications to the cross-correlation and neural networks methods.

This study focused on real-time military applications to meet possible needs in the fight against snipers. Automating detection and classification procedures can effectively integrate software and hardware requirements to estimate shooters' direction of arrival. By having information about the direction of fire, soldiers can enjoy greater protection against lethal threats as they can better seek cover or neutralize snipers.

This study sought to compare and optimize algorithms to detect shot signals. As the cross-correlation method based on [7] lacked a clear methodology to distinguish SW from MB, we used more reference signals and a classification scheme based on RBF SVM

Kernel. However, the method still faced difficulties to clearly differentiate the SW components. Spectral energy analysis, as in [17], obtained no good results in classifying shots since its effectiveness depended on the characteristics of the weapon and the geometry of the environment (relative positions of the shooter, target, and microphone). The SNR in [18] robustly detected impulsive signals but lacked improvement in MB component classification, the most relevant information for the considered applications. Finally, the neural networks in [19] failed to clearly distinguish detection from classification. To improve it, this research suggested the detection process in [18], in which the methodology in [17] served to obtain the classification criterion. This study considered this method, with the suggested adaptations, as the most appropriate for the purpose of this study, resulting in a higher MB success rate of the four methods.

This study used two-layer feed-forward neural networks on Matlab® Classification Learner. A possible extension of this study on the state of the art of methods to detect and classify shot signals could investigate deep and convolutional neural networks to process shot signal spectrograms. This approach can open new perspectives to improve these methods and apply them in practical combat situations.

The use of the method we found the most effective for recordings from rural environments, such as shooting ranges and instruction camps, in a second dataset containing shots from an urban environment, brought new perspectives on the applicability of this technique. Despite the good results from training in a rural environment, the use of this method in urban scenarios offers additional challenges and requires specific training with signals in the latter context. Using a hybrid training for rural and urban settings reduced TPR from 3.7 (urban setting) to 5.3% (rural setting) when compared to training and testing in the same setting.

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