

# Detection of Gunshots from Small Arms

Ondřej Nesvadba  
Brno University of Technology  
Department of Radio Electronics  
Brno, Czech Republic  
xnesva08@vutbr.cz

**Abstract**—This paper deals with acoustic gunshot detection from small arms primarily for use in urban areas. Key part of the paper is an examination of typical features of gunshot signals. Based on the short-term features detection algorithms are proposed in the time and frequency domains. Training and evaluation of the algorithms was performed using real gunshots, non-gunshots as well as synthetic gunshots. The non-gunshots set contains impulsive acoustic events such as dog barking, glass breaking, car horn, etc.

**Keywords**—detection, detection algorithms, frequency domain, gunshot, gunshot parameters, small arms, time domain

## I. INTRODUCTION

This paper deals with the issue of automatic gunshot detection, especially in urban areas with high crime rates. The goal is to propose a comprehensive system that recognizes a gunshot from other impulsive background sounds, such as breaking glass, car horn or barking dog. The main motivation for this study is to develop a system that reliably detects gunshots and immediately sends an alarm message to the responsible authorities.

In general, automatic gunshot detection can be deployed in three principle different scenarios according to the surrounding environment, namely: detection in open space (i.e. nature), detection in urban areas and detection in indoor environments. The purpose of detection in open space is often to protect against poachers [1] [2] or for military use [3], while detection in urban areas and in public indoor spaces is mainly aimed at increasing security. A presentation of gunshot detection technologies effective in urban environments can be found in [4]. A surveillance system for detection of gunshots in indoor environment is described, for example, in [5]. A comparison of successful detection algorithms can be found in the proceedings of the “Detection and Classification of Acoustic Scenes and Events” competition, which was focused on sound detection and the target events were gunshots [6]. Some simple gunshot features, which need relatively low computational time, are proposed in [7].

Focus of this paper is to identify real gunshots in urban environments. For that, analysis of signal waveforms and knowledge of basic gunshot characteristics are needed in order to distinguish real gunshots from other highly impulsive signals that sound similar. From the practical point of view, it is important to eliminate false alarms [8]. To achieve high reliability, fake synthetic gunshots were also examined and compared to the real ones.

## II. GUNSHOT CHARACTERISTICS

Gunshot itself is a very complex physical phenomenon. When the trigger is pressed, multiple signals are propagating through the surrounding. Two most important of these signals are the muzzle blast and the shock wave. A muzzle blast is an audio signal that propagates directly to the microphone. The best way to record a muzzle blast is when the microphone is on the axis of the gunshot. On the other hand, if the microphone is behind the weapon, the muzzle blast is attenuated. A shock wave can be created when the shot is supersonic. The way of shock wave is conical in the direction of the gunshot, so the microphone placed behind the weapon does not pick up the signal at all.

To record a gunshot, only one microphone is necessary. The ideal position is, as already mentioned, right in the axis of the gunshot. However, the more microphones are used, the more information can be obtained. Using four microphones, we can deduce the speed and direction of the gunshot and even the location of the shooter, which can be very helpful in finding the criminal. This issue is not included in this study, but the identification of the shooter’s position is in view as a logical extension of this work in the future.

The gunshot signal has a characteristic waveform shown in Fig. 1. It has its typical N-shaped part. The whole gunshot lasts about ten milliseconds. The gunshot is highly impulsive and its duration is very short with few significant extremes at the beginning. This distinguishes it from other sounds in the time domain. They are usually not that short with the first three to five extremes being so significant.

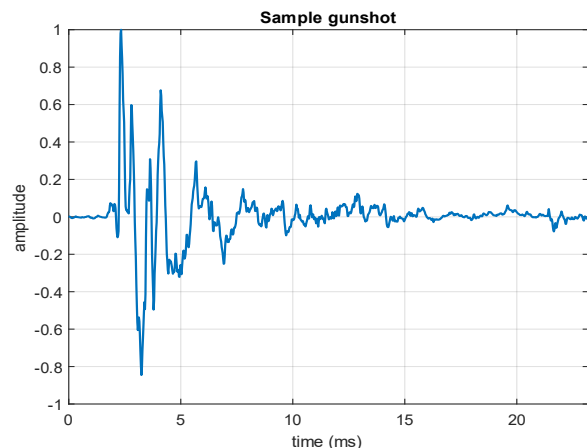


Fig. 1. Example of a typical gunshot waveform.

### III. METHODS FOR GUNSHOT DETECTION

In this section, a few methods used commonly for gunshot detection and used in this study as well will be theoretically introduced. We can analyze signals in time domain or frequency domain. This is the same for gunshot detection. Even algorithms proposed further in this paper are both in time domain as well as in frequency domain.

#### A. Correlation

Correlation is probably the most important and most commonly used method in time domain. It expresses a similarity of two examined signals. In [9], correlation was stated as the most successful method for gunshot detection. For the proposed algorithm, we need a sample signal of gunshot. Other examined signals are afterwards correlated with the sample signal. As a sample signal, self-recorded gunshot from [10] was chosen. Correlation is defined as

$$R_{fg}(t) = \int_{-\infty}^{\infty} f^*(\tau)g(t + \tau)d\tau \quad (1)$$

where  $f$  and  $g$  are correlated signals and  $\tau$  is mutual time shift.

#### B. Fourier Transform

To investigate the gunshot signals in the frequency domain, the spectrum of the signals was calculated by the Fourier transform defined as

$$S_{(\omega)} = \int s(\tau)e^{-j\omega\tau}d\tau \quad (2)$$

where  $S(\omega)$  is spectrum of signal  $s(t)$ . When spectrum is created, further spectral analysis can be done like spectrum energy or spectral entropy. A comparison of the spectra obtained from gunshot and bottle break is shown in Fig. 2.

### IV. DETECTION PARAMETERS

Key part of the whole study is extraction of typical values from gunshot and non-gunshot recordings. From these values, parameters of detection algorithms are determined.

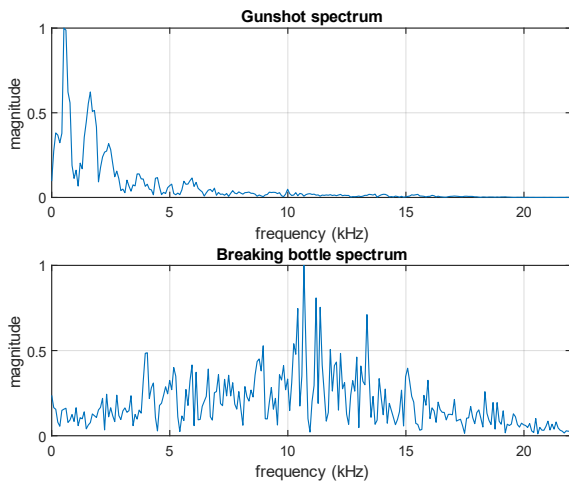


Fig. 2. Example of gunshot and non-gunshot spectrum.

First step was to obtain signals from recordings. That was processed in Matlab. From each recording, two signals were made. Firstly, longer signal of 20 480 samples with the whole gunshot lasting (further called “Sig”) and then shorter signal of 512 samples centered around the maximum amplitude of the gunshot (further called “Shot”). To be unified, signals were standardized to the maximum amplitude equal to one. From those unified signals, further described parameters were computed using Matlab.

#### A. Average Signal Energy

First parameter was an average spectral energy. As gunshots are impulsive, the energy is high, but only in short time section. That means average energy, especially of the longer “Sig”, is not so high. On the contrary it is low compared to the shorter “Shot”. That will be used in one of the algorithms. Other reason for using this parameter is simple differentiation from signals without any impulse.

#### B. Correlation with Sample Signal

Correlation seems to be the most important parameter for the time domain-based algorithm. Signal under test is correlated with sample signal and sum of the correlation is computed. The higher the value is the more similar signals. We apply correlation only for shorter “Shot”.

#### C. Energy Distribution

This parameter is related to the average signal energy. Number of samples of the signal that have larger value than 75 % of maximal amplitude is computed. The number should be smaller for gunshots because of short duration of the impulse.

#### D. Spectral Energy

As gunshot is short impulse, the spectrum is not very rich. There are only a few spectral components close to the beginning of whole spectrum. That means spectral energy should be low. That is one of the parameters of frequency domain-based algorithm. Other non-gunshot recordings have richer spectrum therefore greater spectral energy.

#### E. Spectral Difference

Similar to correlation, we use sample signal to this parameter as well. Spectrum of sample signal is created, then spectrum of examined signal is created and finally the difference of those two spectrums is computed. The difference should be very small for a gunshot and on the other hand quite high for non-gunshots.

#### F. Sig-to-Shot Ratio

As mentioned, average signal energy of gunshot is high for shorter “Shot” but quite low for longer “Sig” because of very short duration if the impulse. That means ration between those two values should be high. At least a lot higher than for vast majority of non-gunshot recordings. This parameter will be used as main detection parameter for one of the algorithms.

### G. Summary of the Parameters Obtained

From the values obtained from gunshot and non-gunshot signals, parameters for detection algorithms were determined and the summary of all the parameters are shown in Table 1. Each parameter is assigned to algorithm, in which it is used.

### V. DETECTION ALGORITHMS

Three detection algorithms were proposed and tested. One is based on time domain, one is based on frequency domain and the last one is based on ratio between longer and shorter parts of gunshot signal (Sig-to-Shot ratio).

When an unknown recording is tested, at first unified signals “Sig” and “Shot” are created and all parameters are computed. Then the algorithm compares the computed values of examined signal with the reference parameters as stated in the summary Table 1. If the values of examined signal meet all the conditions Table 1, the recording is claimed as gunshot. A flowchart of each algorithm is shown in following figures.

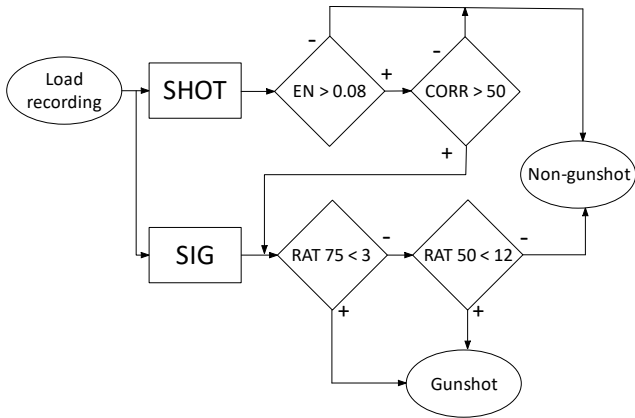


Fig. 3. Flowchart of time domain-based algorithm.

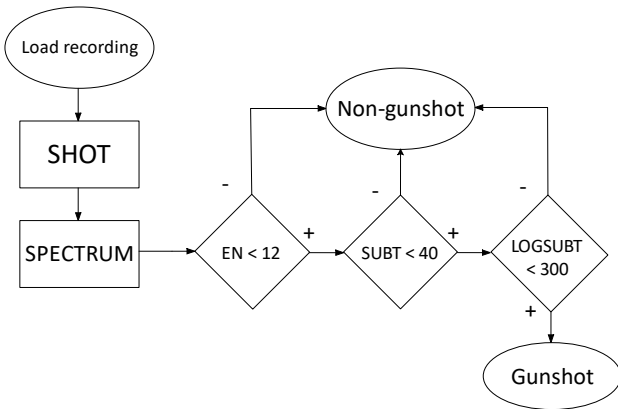


Fig. 4. Flowchart of frequency domain-based algorithm.

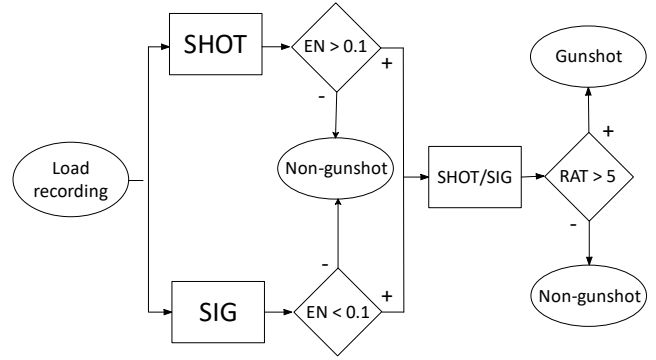


Fig. 5. Flowchart of algorithm based on Sig-to-Shot ratio.

TABLE I. SUMMARY OF PARAMETERS.

| Summary of parameters |                                 |        |
|-----------------------|---------------------------------|--------|
| Algorithm             | Parameter                       | Value  |
| Time domain           | Average signal energy           | > 0.08 |
|                       | Correlation                     | > 50   |
|                       | Energy distribution 75%         | < 3    |
|                       | Energy distribution 50%         | < 12   |
| Frequency domain      | Spectral energy                 | < 12   |
|                       | Spectral difference             | < 40   |
|                       | Logarithmic spectral difference | < 300  |
| Sig-to-Shot ratio     | Average “Sig” energy            | < 0.1  |
|                       | Average “Shot” energy           | > 0.1  |
|                       | Sig-to-Shot ratio               | > 5    |

### VI. OBTAINED RESULTS

The three described algorithms were finally tested on a set of signals covering nine real gunshot signals from 9 mm arm pistol and eight non-gunshot signals including white noise, car horn, dog barking and five glass breaking sounds. Furthermore, two recordings of fake synthetic gunshots, which sound very similar to real gunshots, were tested. All signals used in the experiments were single-channel sounds, sampled at 44.1 kHz and quantized by 16 bits. All recordings were in WAV format.

All proposed algorithms were mostly successful while frequency domain-based algorithm was the best one. All three algorithms successfully detected eight from nine gunshots while vast majority of non-gunshots were ignored. There was one signal, initially considered as real gunshot, which was not detected by any of the algorithms and its waveform was highly extraordinary. It was later decided not to include this signal because it worsened the overall results due to the corrupted recording. Important result is that both fake synthetic gunshots were correctly ignored by all three algorithms. Recordings that sound similarly can be distinguishable by proposed algorithms because their waveform never fully equals to the real gunshots.

TABLE II. SUCCESS RATE OF ALGORITHMS.

| Summary of algorithms |             |                  |                   |
|-----------------------|-------------|------------------|-------------------|
| Criterion             | Time domain | Frequency domain | Sig-to-Shot ratio |
| TPR                   | 89 %        | 89 %             | 89%               |
| FPR                   | 10 %        | 0 %              | 20 %              |

Table 2 shows success rate of all algorithms. The criterion TPR (true positive rate) is percentage of correctly detected gunshots from all tested gunshots. The criterion FPR (false positive rate) is percentage of incorrectly detected non-gunshots from all tested non-gunshot recordings.

For comparison, two gunshots are displayed below. It is the waveform of a real gunshot (Fig. 6) and a fake synthetic gunshot (Fig. 7), where the difference is clearly visible.

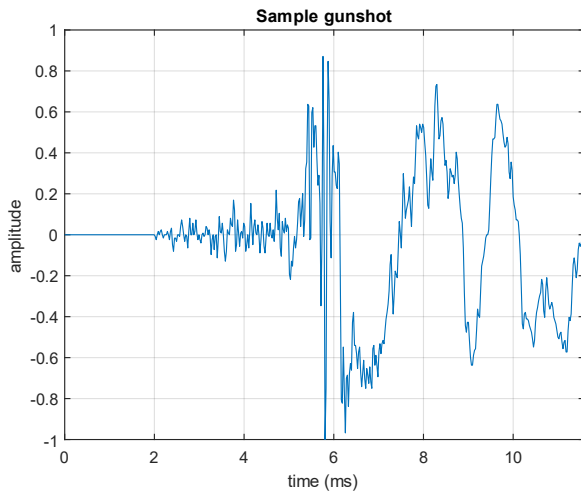


Fig. 6. Real gunshot waveform.

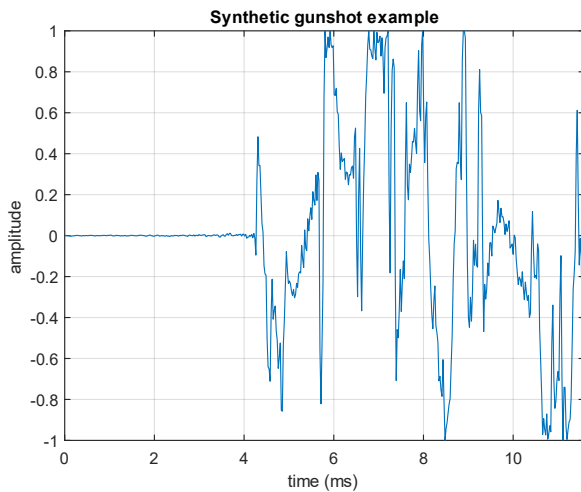


Fig. 7. Fake synthetic gunshot waveform.

## VII. CONCLUSION

Three algorithms were proposed to detect of real gunshots while ignoring background noise and other impulsive sounds, as well as fake synthetic gunshots. All algorithms succeed with a success rate of 80 %. By combining these algorithms, a comprehensive detection system can be developed for security purposes in high crime urban areas.

There is also an idea of a mobile application implemented into smartphones as in [11] with detection algorithms that will be able to detect a gunshot and immediately inform the responsible authorities. The more users the application would have, the more information would be obtained. If this application would be used by more users in surrounding of a shooter, the location of the shooter can be easily determined.

In near future, it will be necessary to enlarge our sound database by adding recordings of other types of impulsive sounds and non-stationary noise [12] potentially found in urban environments. Furthermore, it will be useful to mix gunshots with background sounds such as traffic noise, music and human voice.

## REFERENCES

- [1] G. Kalmar, G. Wittemyer, P. Völgyesi, H. B. Rasmussen, M. Maroti, and A. Ledeczki, "Animal-borne anti-poaching system," in *Proc. Int. Conf. on Mobile Systems, Applications, and Services*, Seoul (South Korea), 2019, pp. 91–102.
- [2] M. Sigmund and M. Hrabina, "Efficient feature set developed for acoustic gunshot detection in open space," *Journal Elektronika ir Elektrotechnika*, vol. 27, no. 4 pp. 62–68, 2021.
- [3] J. A. Mazurek *et al.*, "Boomerang mobile counter shooter detection system," in *Proc. of SPIE – The International Society for Optical Engineering*, vol. 5778 (PART I), Orlando (USA), 2005, pp. 264–282.
- [4] J. R. Aguilar, "Gunshot detection systems in civilian law enforcement," *Journal of the Audio Engineering Society*, vol. 63, no. 4, pp. 280–291, 2015.
- [5] S. U. Rahman, A. Khan, S. Abbas, F. Alam, and N. Rashid, "Hybrid system for automatic detection of gunshots in indoor environment," *Multimedia Tools and Applications*, vol. 80, pp. 4143–4153, 2021.
- [6] *Detection and Classification of Acoustic Scenes and Events* (competition website). [Online]. Available: <http://www.cs.tut.fi/sgn/arg/dc2017/>
- [7] M. Hrabina and M. Sigmund, "Gunshot recognition using low level features in the time domain," in *Proc. of International Conference Radioelektronika*, Praha, 2018, pp. 1–5.
- [8] J. Bajzik, J. Prinosil, R. Jarina, and J. Mekyska, "Independent channel residual convolutional network for gunshot detection," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 4, pp. 950–958, 2022.
- [9] A. Chacon-Rodriguez, P. Julian, L. Castro, P. Alvarado, and N. Hernández, "Evaluation of gunshot detection algorithms," *IEEE Transactions on Circuits and Systems*, vol. 58, no. 2, pp. 363–373, 2010.
- [10] M. Hrabina and M. Sigmund, "Acoustical detection of gunshots," in *Proc. of International Conference Radioelektronika*, Pardubice, 2015, pp. 150–153.
- [11] D. Welsh and N. Roy, "Smartphone-based mobile gunshot detection," in *Proc. of the 2017 IEEE International Conference on Pervasive Computing and Communications Workshops*, Kona (USA), 2017, pp. 244–249.
- [12] P. Zelinka and M. Sigmund, "Hierarchical classification tree modeling of nonstationary noise for robust speech recognition," *Information Technology and Control*, vol. 39, no. 3, pp. 202–210, 2010.