Gunshot Classification from Single-channel Audio Recordings using a Divide and Conquer Approach

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Abstract: Gunshot acoustic analysis is a field with many practical applications, but due to the multitude of factors involved in the generation of the acoustic signature of firearms, it is not a trivial task, especially since the recorded waveforms show a strong dependence on the shooter's position and orientation, even when firing the same weapon. In this paper we address acoustic weapon classification using pattern recognition techniques with single channel recordings while taking into account the spatial aspect of the problem, so departing from the typical approach. We are working with three broad categories: rifles, handguns and shotguns. Our approach is based on two proposals: a Divide and Conquer classification strategy and the inclusion of some novel features based on the physical model of gunshot acoustics. The Divide and Conquer strategy is aimed at improving the rate of success of the classification stage by using previously retrieved spatial information to select between a set of specialized weapon classifiers. The minimum relative error reduction achieved when both proposals are used, compared with a single-stage classifier employing traditional features is 38.7%.

1 INTRODUCTION

Gunshot acoustic analysis has practical applications in many fields such as forensics, security, gun control or military tactics to name a few. The acoustic signature produced by explosive propelled weapons, particularly small firearms, has been the subject of study for some decades (Weissler and Kobal, 1974; Fansler et al., 1993; Maher, 2007). Nevertheless, gunshot acoustic processing has become even more important in recent years, mainly due to the development of sniper detection systems (Kawalec et al., 2006) aided by sensor fusion techniques.

Renewed interest in this topic has yielded multiple approaches to gunshot detection over the last decade. Most of the existing proposals use pattern recognition techniques such as Gaussian Mixture Models (GMM) or Support Vector Machines (SVM) (Freire and Apolinário Jr, 2010; Ahmed et al., 2013) in conjunction with classic acoustic analysis features, although there are also examples in the literature that use different methodologies (Sergent and Winkler, 1995). On the other hand, acoustic weapon classification has not been widely studied yet, with only a few available precedents (Khan et al., 2009; Sallai et al., 2011). Other than detection itself, most of the existing strategies to obtain additional information from the recorded signals rely on physical measurements taken at different locations. It is common to employ temporal differences between the detection of an event over a group of sensors to locate the shooter or estimate the trajectory of the bullet by triangulation (Millet and Baligand, 2006).

One of the main concerns in this field is the strong dependence of the recorded waveforms on the shooter's position and orientation, mostly because the acoustic disturbance created by the explosive propeller is highly directional (Maher and Shaw, 2010). This fact means that even when dealing with the same weapon, the perceived sound has a strong spatial component so that recordings from two distant locations can be completely dissimilar.

In this paper, we tackle acoustic weapon classification from a novel approach. The main novelty resides in the extraction of spatial information from single-channel recordings, with the purpose of obtaining better generalization.

We are working with three broad categories: rifles, handguns and shotguns. Our approach is based on a Divide and Conquer (D&C) strategy (Parvin et al., 2011) aimed at minimizing the classification error by taking advantage of less demanding problems to select between a set of specialized classifiers. The objective is to overcome the uncertainty produced by the

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lack of spatial references. As a way to balance out the loss of information derived from the use of single channel signals we have reformulated the spatial problems addressed in this field to be able to solve them without a multichannel setup. Weapon classification is aided by the solution of three additional problems: detection of the shock wave produced by supersonic projectiles, and a binary estimation of the proximity both to the shooter and to the trajectory of the bullet (range & alignment).

In our proposal, the shock-wave detection stage is employed to extract a small set of novel features based on its acoustic model, while range and alignment estimators are responsible for performing spatial division to select the most suitable classifier for the last stage.

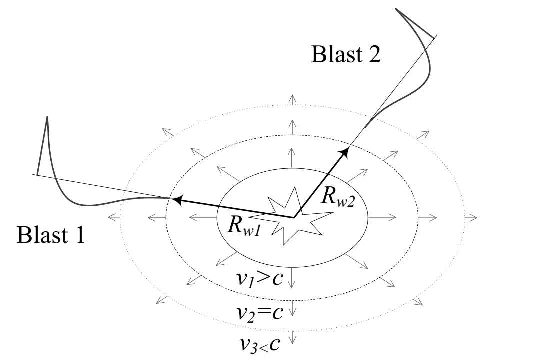

Figure 1: Differences in blast wave radiation from an ellipsoid volume at two points.

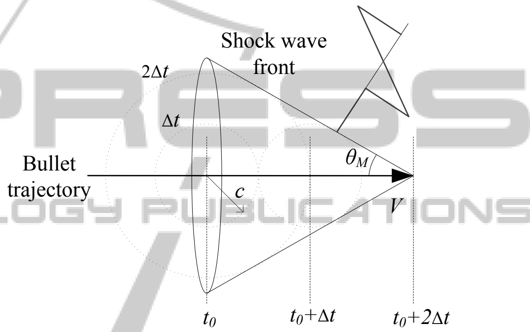

Figure 2: Geometric model of shock wave propagation.

2 ACOUSTIC MODEL

Before addressing the particularities of the presented problem, it is worth making a brief overview of the main elements that play a role in the composition of a gunshot acoustic signature.

2.1 Muzzle Blast

Common firearms produce their characteristic sound as a result of the sudden expansion of gases generated at the end of their barrel by the explosive charge employed to propel the projectile, formally known as *muzzle blast*.

A simple approach that can be used to understand the acoustical excitation produced by this kind of phenomenon is *Weber's spectrum* model, accounted for in ISO norm (ISO-CEN.17201-2, 2006). This model gives us an estimation of the Fourier spectrum of a blast wave on free air (Freytaga et al., 2006) as a function of the radius of the expanding gas sphere created by the charge in the precise instant that its propagation speed decreases enough to match the speed of sound c. The energy of the explosion is directly related to the volume of displaced gases, shifting the spectrum to lower frequencies as the radius of the sphere increases.

However, in the case of firearms, the constraining effect of the barrel on the expansion of gases has a big impact on the produced sound, making the muzzle blast strongly directional. Applying Weber's radius model, this directionality can be explained as a result of the divergence in the expelled gases shape from a perfect sphere, implying a dependence between the listener location and the perceived radius (Karl Wilhem Hirsch, 2013). Figure 1 shows the differences in the blast waves created by an ellipsoid volume as a function of the perceived radius.

2.2 Projectile Shock Wave

The second main component of a gunshot acoustic signature is the *shock wave* produced by a projectile traveling at supersonic speed.

For a projectile with a velocity $V > c$, and defining *Mach number* as $M = V/c$, the generated shock wave propagates in conic shape forming an angle $\theta_M = arcsin(1/M)$ with the trajectory of the bullet, as shown in Figure 2. This acoustic disturbance is commonly referred as *N-wave* due to its characteristic geometry resembling a capital letter "N". Its most relevant parameter, its duration T, can be approximated by knowing the physical dimensions of the bullet, its velocity and the closest distance between the microphone and the projectile trajectory (Maher, 2006).

While the muzzle blast can be seen as a global event, due to the extensive range reached by the generated acoustical excitation, the shock wave has a local influence, since its appearance only takes place for those positions close enough to the trajectory of the bullet.

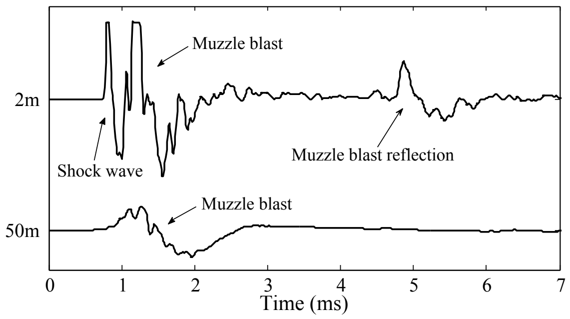

Figure 3: Recorded pressure waveforms for a .45 caliber handgun at two locations.

2.3 Additional Components

The aforementioned components are the main ingredients of a gunshot acoustic signature. However in a real scenario, the recorded waveform may be very different from the ideal model. In the case of close range recordings, ground reflections from both muzzle blasts and shock waves, along with the characteristic sound produced by the firing mechanism of the weapon are most likely to be present, which can be a problem in the event that they overlap with the direct signal. On the other hand, in the case of long range recordings, the influence of the propagation path has a tremendous impact on the received sound, due to the short duration of these waves that makes them act as impulses, in addition to appearance of a vast range of acoustical phenomena such as absorption, spreading, attenuation, etc.

Other than these effects, non-idealities on the recording equipment can also produce some artifacts, the most notorious being saturation given the high sound pressure levels created by muzzle blasts that commonly exceed 140 dB.

Figure 3 illustrates various of this effects with two recordings of the same weapon extracted from our database.

It is worth mentioning that the uncertainty produced by the directivity of the muzzle blast and the appearance of undesired acoustic phenomena, commonly make the differences between recordings of a same weapon at two distant locations greater than those of two distinct weapons captured at the same position.

3 CLASSIFICATION SYSTEM

When approaching gunshot acoustic analysis there are three main questions to be asked: which weapon has been fired, where is the shooter and what is he/she targeting. These problems can be reformulated, employing more adequate terms, into the problems of weapon classification, shooter localization and bullet trajectory estimation. From these three problems weapon classification is the only one that does not require some degree of spatial diversity, making it the most suitable to tackle using single channel recordings.

Instead of focusing on differentiating between particular gun models, weapon classification is being performed by categories, namely handguns, rifles and shotguns. In this way, the physical differences (barrel length, caliber, propellant amount, etc.) between the weapons inside each classification group are less significative than those with the rest of the population. By using broad categories, the usage of the database is more effective since there is more available data on each class and they are better balanced for the tests.

It is worth mentioning that proper detection is required in order to perform classification. Since we are focusing on weapon classification, we work on an assumption of perfect detection. As previously stated, there are multiple gunshot detectors capable of achieving good performance rates already available in the literature.

The classification is performed using Least Squares Linear Discriminant Analysis (LS-LDA) (Ye, 2007).

3.1 Feature Set

For the main feature set we are using a signal segment of length 10.7 ms (1024 samples) containing the Muzzle blast. This segment is automatically selected by the system, using a moving average of the energy of the signal. Since the muzzle blast is always appearing (perfect detection is assumed) and it is the main source of energy, a secondary energy source preceding it with a lower energy level has to be an N-wave. (see Figure 4 for a visualization of this situation). The moving average is computed using a moving square window of length 64 samples over the squared input signal and from it the starting point for the Muzzle blast segment is selected from the absolute maximum.

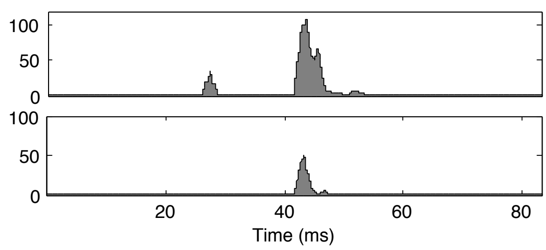

Figure 4: Energy moving average of two gunshots recorded at the same position. (top) Rifle (bottom) Handgun.

Once the segment is selected, we estimate its spectral density with a periodogram using the *Fast Fourier Transform* (FFT). From this estimation, we compute 16 Mel-frequency Cepstral Coefficients (MFCCs) (Hunt et al., 1980) to be used as features. By doing this we obtain a perceptual representation of the spectral characteristics of the signal compressed in a much smaller number of values. MFCCs have demonstrated that they are a valuable asset for general acoustic analysis on numerous occasions, and they are also used in gunshot detectors from Freire et al. and Ahmed et al. among many other applications. In addition to MFCCs three additional features are extracted from the stored peak values.

From the selected segment we calculate its energy level in decibels and from the FFT we extract two spectral descriptors namely kurtosis and roll-off.

The classification feature set is composed of 19 features:

- 16 MFCCs
- Signal energy (in decibels)
- 2 Spectral descriptors:
  - Kurtosis
  - Roll-off

4 PROPOSED CLASSIFICATION STRATEGIES

In this work we are addressing the problem of weapon classification departing from a multichannel approach in favor of single channel processing. Nonetheless, this decision implies a significative reduction of the available information on the events, specially since we can no longer use triangulation based techniques to solve the spatial problems that could help in the classification stage. To address this issue we have reformulated the initial problems, turning them into simpler problems that do not require the use of multiple information sources to be solved. However these new objectives are notably influenced by the coverage of the available database as we will later explain.

Recording at a single location suppresses the capability of triangulating the exact shooter's position. However we can still provide some vital information on the event by making a classification of his proximity to the sensor. In the current implementation, we are discerning between close range ($d < 20m$) and medium range ($d > 20m$) discharges, as the employed database does not contain any long range recordings. Nevertheless, the proposed methodology is valid for any range.

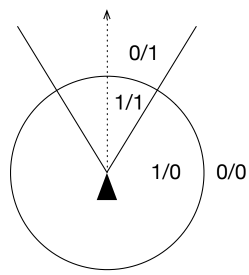

Figure 5: Schematic representation of the spatial division provided by the first classification stage (range/aligment).

Trajectory estimation also suffers from the lack of spatial references. This estimation has been replaced by the ability to classify the proximity of the sensor with the trajectory followed by the bullet into two broad alignment categories: on-axis and off-axis. On-axis implies that the microphone location is inside a 30 degree cone within the actual trajectory of the bullet, while off-axis represents any other position.

In addition to these, we can obtain some additional information from N-wave detection, since shock-wave appearance is related both to the fired weapon and to the relative range and aligment of the recording. N-wave detection does not present any particularity since it is commonly performed over single channel signals even in distributed systems since the detection usually takes place locally at each node. However this stage is also employed to extract a small set of features adapted to the particularities of the problem.

Finally, we want to highlight that the different problems described do not present the same level of complexity: range estimation is the easiest and weapon classification is the most difficult. Bearing this in mind, it should be beneficial to employ the most likely to be true knowledge on the signal, to aid the decision making for the more likely to fail using a *Divide and conquer* (D&C) strategy. D&C aims at reducing the complexity of a problem by analyzing a broken down version of itself, what in our case is performed by employing the outcomes of the three easier problems to aid in the solution of the most demanding. N-wave detection is used to add new information to the problem while range and alignment estimators are used to divide the space in four regions, according to Figure 5. Each of these regions are analyzed independently with an specialized weapon classifier.

4.1 D&C Classifier Tree

We propose to use a D&C classification tree, by using the outcome of two spatial classifiers to select between a set of specialized weapon classifiers that

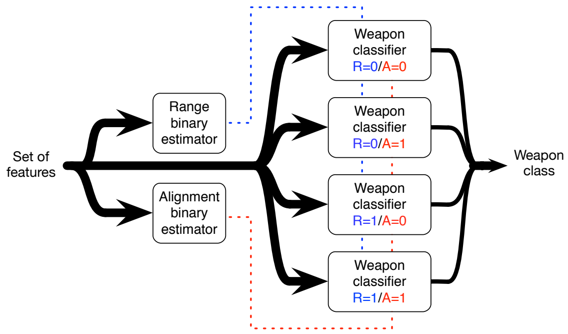

Figure 6: Simplified diagram of the D&C Classifier tree.

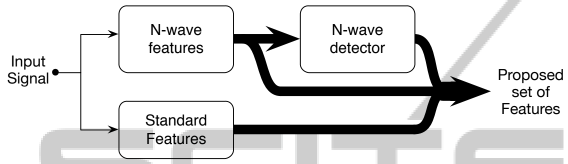

Figure 7: Simplified diagram of the proposed feature extraction system.

assume the veracity of the preceding decisions. The first stage of the classifier tree is in charge of range and alignment binary estimation, whereas the second stage takes the decision on weapon category. Each of the classifiers in the decision tree are implemented with LS-LDA. The specialized classifiers are designed using a specific subset of events, so that they do not contemplate the existence of the other branches. A simplified diagram of the D & C scheme is shown in Figure 6. Notice that in the classification tree only one specialized classifier is active at a time.

4.2 N-wave Based Features

The N-wave detector is not included in the decision tree. Instead it is devised to extract some novel features related to the shock wave that are later included into the main feature set. In the same way as the classifier tree, the N-wave detector is implemented with LS-LDA. This proposal relies on two feature sets, one for the N-wave detector and one for the main classification, although some novel features are shared by both sets. See Figure 7 for a schematic representation of the feature integration between stages.

4.2.1 N-Wave Detector Features

For the N-wave detector feature set, we are using a signal segment containing the first 10.7 ms (1024 samples) of the event that is automatically selected by the system. This selection takes place using an algorithm that scans the input signal to find all local peaks larger than one-third of its absolute maximum. The

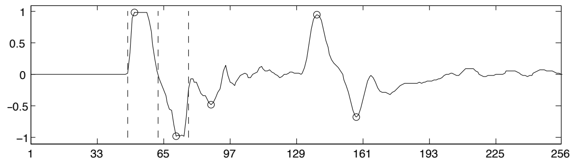

Figure 8: Selected signal segment (first half) and reference points for feature extraction at the N-wave detector.

location of the first found peak sets the starting point for the selected segment (with an offset of 50 samples). Additionally amplitude and index values for all peaks are temporarily stored. From the selected segment we compute its FFT to obtain 16 MFCCs.

Since supersonic shock waves have a very relatable shape in the time domain (hence the name N-wave) it should be advisable to employ some of their temporal features to perform the detection. N-waves typically range between 200 and 300 μs and have a high degree of symmetry between their half cycles. Other than that, in the event of existing, the N-wave is always the first component to reach the microphone. Knowing these facts and having already found the local peaks of the signal we can use their values to compute some shape descriptors to be used as features. Notice that there are N-wave detectors that work with this kind of temporal measurements alone without resorting to advanced pattern recognition techniques (Sallai et al., 2011).

Taking the index value of the first two peaks and subtracting them we get a representative value of the duration of the first wave, whether it is an N-wave or not. From these same peaks we can also find the zero-crossing points of the wave, that can be used to calculate the half cycle duration ratio as a way of measuring its symmetry. The last value extracted is the energy of the alleged N-wave between its start and finish points (zero-crossings). Figure 8 shows an N-wave segment automatically selected by the algorithm and its different reference points.

The complete N-wave detector feature set is composed of 19 features:

- 16 MFCCs
- 3 N-wave descriptors:
  - Duration
  - Half cycle ratio
  - Energy

4.2.2 Proposed Feature Set

Instead of using the N-wave detector output to further divide the classification tree, we propose to use it as an additional feature. The raw output of the detector (without thresholding) is added to the classification feature set together with N-wave half cycle ratio and duration previously obtained for the detector feature set.

In addition to this, at the main feature extraction stage, we calculate the temporal difference between energy clusters (see Figure 4) since it represents the Time Difference of Arrival (TDoA) between the N-wave and the muzzle blast. The obtained TDoA is used as a feature, however in the case that only one source exists, this parameter is set to a default value (zero).

The proposed classification feature set is composed of 23 features:

- 16 MFCCs
- Signal energy (in decibels)
- 2 Spectral descriptors:
    - Kurtosis
    - Roll-off
- 4 N-wave descriptors:
    - Time Difference of Arrival
    - Duration
    - Half cycle ratio
    - N-wave Detector output

5 EXPERIMENTAL WORK AND RESULTS

In order to test the performance of the proposed system and its generalization capability, we have performed different experiments using various classifier configurations, database divisions and resampling strategies.

5.1 Database

Our database contains unprocessed recordings from 14 weapons, divided into 5 handguns, 5 rifles and 4 shotguns. Firing sounds for all the weapons are available at 10 distinct positions with 12 repetitions for each weapon-position combination, adding up to a total of 1680 individuals registers.

Of the 10 unique positions, 4 are labeled as short-range and 6 as medium range, whereas 6 are labeled as on-axis and 4 as off-axis. N-waves only appear in 22.1% of the recordings, not appearing at all for 6 of the weapons (2 handguns and all shotguns) since they use subsonic ammunition.

All the signals are professionally recorded at 96000Hz using various high-quality microphones and recording equipment.

5.2 Description of the Experiments

To design and test each classification system for the experiments, the database is divided into two independent subsets, a *design set*, used exclusively for designing the classification system itself, and a *test set*, used for evaluating its performance. It is important to emphasize that under no circumstance is the same pattern contained in both sets at the same time.

The results shown in Tables 1 and 2 are arranged attending to the constraints imposed to the design set in descending order. The term *included* used to describe different sets, refers only to the constraints applied to the design set as follows:

- *Position & Gun not included*: None of the sounds of the tested gun, neither those recordings of the remaining weapons at the tested position have been employed for designing the classifiers.
- *Position not included*: The design set does not contain any of the recordings at the tested position.
- *Gun not included*: The design set does not contain any sound of the tested weapon.
- *Position & gun included*: Only the tested sounds have been excluded from the design set.
- *50/50 database division*: The database is divided in two equally sized random sets each containing 6 of the available events for each weapon-position pair.

Table 1: Obtained weapon classification error for various configurations and design constraints.

	Standard Classifier	Classifier tree
Position & Gun not included		
Standard feature set	56.9%	43.4%
Proposed feature set	45.6%	32.9%
Position not included		
Standard feature set	46.5%	34.6%
Proposed feature set	36.5%	28.5%
Gun not included		
Standard feature set	47.1%	29.3%
Proposed feature set	35.6%	21.4%
Position & Gun included		
Standard feature set	39.9%	21.8%
Proposed feature set	29.5%	16%
50/50 database division		
Standard feature set	35.6%	14.4%
Proposed feature set	20.9%	9%

Table 2: Obtained errors at the first classifying stage for various design constraints.

	Range	Alignm.	N-wave
Position & Gun not included	3.5%	6.9%	8.9%
Position not included	2.7%	6.7%	7.6%
Gun not included	0.6%	2.3%	6.2%
Position & Gun included	0.5%	2.2%	5.5%
50/50 database division	0.5%	1.3%	2.9%

In the first four cases, we have applied a leave-one-out cross-validation technique (LOOCV) (Efron, 1979). The results were obtained averaging the outputs of 140 independent experiments, where the different test sets are formed by the 12 repetitions available for every weapon-position combination. The design set employed for each case is formed by all the remaining sounds in the database not excluded by the imposed constraints.

In the last case, all weapon-position pairs are tested at the same time, the results were obtained averaging 1024 random database divisions in two equally sized sets.

Table 1 shows the effect of the adopted strategies in the classification error. For each database division there are 4 results, obtained with different configurations. The first 2, labeled as *Standard classifier* were obtained with a single classifier without the proposed D&C scheme, while the other 2 labeled as *Classifier tree*, take advantage of the suggested specialized classifier configuration. Additionally, for both configurations 2 different sets of features were tested: *Proposed feature set* including the novel features presented in this paper, and *Standard feature set* that excludes them.

Table 2 shows the errors obtained for the N-wave detector and the first stage of the D & C Classifier tree for the different database divisions when using the proposed feature set.

5.3 Discussion of the Results

The obtained results show a strong dependence between the spatial resolution of the classifiers and the obtained error, understanding spatial resolution in this context, as the number of events contained in the design set with a unique spatial relationship between the recording location and the shooter's position and orientation. However as it is clear from the results for any of the tested constraints, the proposed strategies help to greatly reduce the classification error, even when used individually.

For the worst case-scenario in Table 1, when neither the tested gun nor the tested position were part of the design set, the classification error of a single-stage approach with traditional features reaches 56.9%. This figure is reduced by 20% with the proposed features and by 24% with the specialized classifier scheme. When both proposals are used, the obtained error is 32.9%, a 42% relative reduction over the initial error.

Notice how, even when the objective of the classification is to categorize the weapon, removing the tested position from the design set (so that it does not contain any previous references of that location) has a greater impact than removing the gun itself. Although the relevance of including the tested location on the design set is more clearly shown on Table 2 under range and alignment errors.

We have chosen to use Linear Discriminant Analysis over more "capable" solutions, because nonlinear classifiers have shown an overfitting tendency when dealing with the presented problems, specially in the later weapon classification stage. Nevertheless, the advantage of using specialized classifiers holds true for any of the tested techniques.

6 CONCLUSIONS

In this work we have proposed a novel method for extracting relevant information from single channel gunshot recordings, departing from the typical multichannel approach.

We have shown that information retrieval from single channel gunshot recordings is a feasible option, specially when using an adequate feature set adapted to the particularities of the scenario. We also show how D&C strategies can be applied to simplify the complexity of the problem. The minimum relative error reduction achieved combining both proposals when compared with a single-stage classifier with traditional features is 38.7%.

The next experiments should be conducted increasing the spatial coverage of the database to include a broader spectrum of locations and orientations. Anyhow, further research is required to find new solutions in order to address the variations on the recorded waveforms produced by the directivity of the muzzle blast and the influence of the environment since they represent the main source of uncertainty.

Despite the lower performance in comparison to multichannel systems, single channel gunshot analysis is a valuable tool for forensics and other applications where specialized hardware is no available, and could also serve as a backup strategy for distributed systems in case of a communication failure

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