SIAMESE BALLISTICS NEURAL NETWORK

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ABSTRACT

Firearm identification is crucial in many investigative scenario. The crime scene often contains traces left by firearms in terms of bullets and cartridges. Traces analysis is a fundamental step in the Forensics Ballistics Analysis Process to identify which firearm fired a specific cartridge. In this paper we present a fully automated technique to compare cartridges represented as a set of 3D point-clouds. The overall approach is based on Siamese Neural Network learning paradigm that we use to build a suitable embedding space where the 3D point-cloud of the cartridges are compared. The proposed approach has been assessed by considering the NBTRD dataset. Obtained results support the exploitation of the proposed technique in ballistic analysis.

***Index Terms*—** Image Forensics, Siamese Network.

1. INTRODUCTION

Crime scenes are often populated by evidences like cartridges and bullets. The analysis of these evidences can lead to the solution of the most criminal cases. Such analysis usually allows the collection of observations of traces imprinted by the firearm on different sections of the cartridges. The traces impressed on cartridges and bullets after the shot, can be associated to a specific firearm and are considered as a unique fingerprint among the different weapons. The ballistic comparison analysis is performed between the cartridge or bullet found on the crime scene and those obtained using the weapon of the suspected person. As illustrated in Figure 1, a cartridge is composed by several parts. A generic weapon through some mechanical components performs three different phases: loading the weapon, shot and ejecting the cartridge. During the ballistics comparison, trace analysis considers anomalies left by the firing pin, the extractor, and the once related to weapon breech face. The bullets comparison is instead made by analyzing the striations left by the helical grooves of the weapon's barrel.

Starting from 1990s, the comparison is made through visual inspection employing an optical instrument useful to compare microscopic features on cartridge pairs. This analysis is performed by experts which zoom and properly observe the cartridges (or bullets) found on the crime scene simultaneously with those shot by probable weapon under suspect. The main limit of this method is that the overall evaluation outcome made by experts is very subjective.

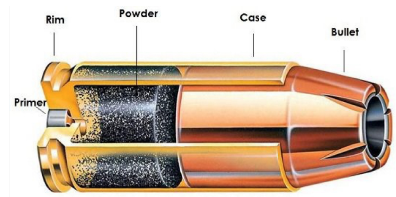

Fig. 1. Anatomy of a cartridge

Over the years, the technologies used for ballistics comparison are rapidly evolving in order to allow a more and more accurate analysis less tied to experts knowledge. The possibility to represent cartridges as 2D images, topography images or 3D point-clouds has opened new research challenges as well as the opportunity to make from manual optical comparison techniques, to more sophisticated semi-automatic or fully automatic digital techniques. The challenge is to develop approaches that lead to an objective evaluation thanks to the availability of sophisticated technologies for both, acquisition and analysis.

In this paper we present a fully automated technique for forensic ballistics cartridge comparison. The technique exploits a cartridge pairs as input represented as a 3D point-clouds obtained with a laser scanner. We design a method which exploits Siamese Neural Networks for fully automatic comparison of 3D point-clouds. The proposed approach outperforms state of the art techniques on the NIST Ballistics Toolmark Research Database (NBTRD) [1].

2. RELATED WORKS

Forensics ballistic is an active research field. Many studies have been performed in this context to address the comparison of cartridges or bullets. Only few of them deal with the analysis of cartridges as 3D point clouds. Banno et al. [2] used 3D data to identify a firearm by means of comparison of impressions left on cartridge surfaces. They used the iterative closest point (ICP) method for the alignment of the 3D shapes related to two cartridges to be compared. To establish similarity or dissimilarity among cartridge pairs a distance measure between the aligned 3D shapes have been considered. Riva and Champod [3] have developed a semi-automated method that is able to take 3D measurements on cartridge. After a manual pre-processing phase, mainly based on image alignment and ad-hoc pre-processing, they computed the likelihood ratios (LR) to compare the firing pin impression and the breech face of two cartridges.

In 2015 the NIST has standardized the forensic ballistics comparison analysis by introducing the Congruent Matching Cells (CMC) method based on the principle of discretization of cartridge images, in order to make more objective the identification process and to obtain an estimation of the error. In late 2016, the NIST Ballistics Toolmark Research Database (NBTRD) was published as an open-access dataset containing 2D and 3D acquisition of bullets and cartridge fired by different firearms. By working on such data different researchers have proposed novel techniques for cartridges comparison and weapons identification.

Morris at al. [4] exploited the NIST dataset to evaluate the performance of the Integrated Ballistics Identification System (IBIS). The system has previously been evaluated on the National Integrated Ballistics Information Network (NIBIN) dataset which is composed by bullets and cartridge fired in crime scenes. In particular, to test IBIS on NIST dataset five standard cartridge cases have been considered with good discrimination performances. Tai and Eddy [5] proposed a fully automated technique for the comparison of the breech face impressions which is based on 2D optical images. The technique is composed by the following main steps: preprocessing, similarity metric computation and uncertainty quantification. The preprocessing phase includes the process of the selection of the breech face marks, the image alignment (because the base of the cartridge case can be slightly tilted on a plane, the removal of circular symmetry (because the cartridge case could have differences in depth that are circular in nature, and hence cause differences in brightness), outlier removal and filtering. The similarity computation is based on the maximum cross-correlation function between two images.

There is not yet consensus for a shared benchmark of the various technique. In Tai and Eddy [5] results were presented by means of the TOP-10 list test (originally proposed in [6]: for each image I the TOP-10 list are the 10 images (present in the reference dataset) with the highest similarity scores when compared against I.

3. SIAMESE BALLISTICS TECHNIQUE

The proposed Forensics Ballistics Analysis is carried out by means of comparison: a selected cartridge is compared to another cartridge found on a crime scene. The goal is to estimate the value $L = \widehat{d}(s_1, s_2)$ where s_1 and s_2 are two cartridge samples with their own impressions left by an unknown firing pin of a gun and $\widehat{d}$ is a function to be modelled for the

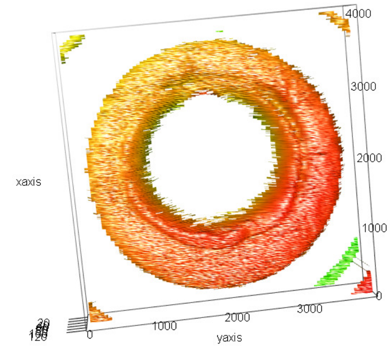

Fig. 2. Breech face impression

correct estimation of the value L. The function $\widehat{d}$ is usually modelled to range in $[0, 1]$. Specifically, L has to be close to 0 if the two considered samples were fired by the same gun (i.e. the cartridge can be considered a forensics evidence). On the contrary, value of L should be close to 1 if the two considered samples were fired by different guns. Also, L should be small in case two samples were fired by guns of the same model.

Our hypothesis is that by considering a 3D point-clouds training set of paired cartridges for which L is known it is possible to learn a function $\widehat{d}$ which approximate the real unknown function d. To this aim in our experiments we considered the dataset NBTRD to learn $\widehat{d}$.

In the NBTRD dataset, each sample $s_i \in R^{n \times 3}$ is a 3D point-cloud obtained by scanning the breech face of a fired cartridge. An example of point-clouds is shown in Figure 2. Usually, points in each point-clouds appear without any specific order (both geometrical and/or logical). The aim is to find a technique to learn d with the following desired properties:

1. robustness to order permutations of points in each point-cloud sample s_i;
2. robustness to geometrical conditions of point-clouds;
3. L should take into account the distribution of neighbourhoods of points;
4. no preprocessing needed, thus invariance of L to point-clouds acquisitions and alignments.

To satisfy all the above properties, point-clouds cannot be processed as they are because the point-cloud representation itself does not infer an ordering for the points to be read. We should choose an arbitrary sorting method for these kind of data but, doing so, not all of the listed properties will be satisfied. For example, one can consider a VOXEL representation [7] of the point-cloud, but in this case two properties will not be satisfied: a sampling/quantization operation is applied and this would cause detail loss moreover initial alignment becomes fundamental and can change drastically the Voxelization process with different output values. Thus we fall into all of the CMC-based algorithms which are heavily dependent on preprocessing.

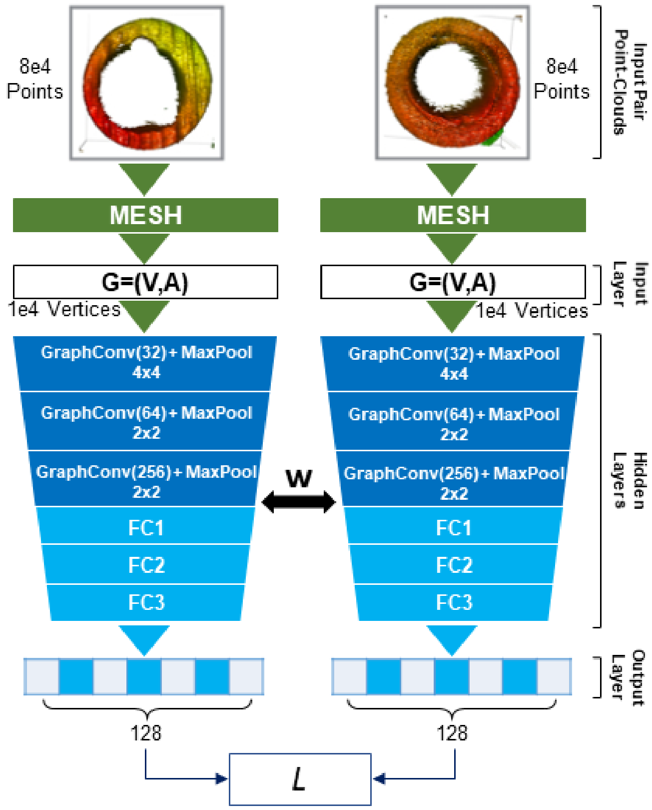

Fig. 3. Siamese Ballistics Neural Network Architecture: given a pair of 3D point-clouds, they are converted into meshes and then encoded into a graph representation. This is the input layer for a Siamese Network exploiting the GraphConv Layer. A 128 dimensional array is the output layer to be used to learn the L distance encoding the difference of the two input point-clouds

In order to define an ordering for point-clouds we transform them into meshes and therefore we exploit a graph representation [8]. From graph signal processing theory we also exploit the concept of convolution between graphs in order to build a Graph Convolutional Layer to be used inside a Neural Network. The proposed technique exploits an ad hoc designed couple of Convolutional Graph Neural Networks combined in Siamese mode to learn L starting from pairs of samples of point-cloud samples. We called this network Siamese Ballistics Neural Network (SBNN).

Simple alignment of point-clouds through standard alignment techniques, like the well-known ICP [9], do not achieve great results due to two main factors: point clouds are very similar and differ just by very few details; the alignment task should be performed not only by reducing an optimal target function but should take into account a number of constraints that experts know and apply during their ballistics investigations. The objective of this paper is not only to build a framework to solve the ballistic studies of fired cartridges, but also to learn how experts do their work. This is done by the SBNN, that demonstrated to be able to understand which part of graphs are more important for comparison by learning an efficient L to compare cartdridges that satisfies all the properties listed above.

In the following subsections each part of the proposed SBNN will be described in details.

3.1. From Point Cloud to Graph representation

We exploited Meshlab [10], a common software for 3D point-cloud editing, to convert point-clouds into meshes. Hence given as input 3D mesh of a cartridge, it can be encoded as a graph:

$$G = (V, A) \tag{1}$$

where each $V \in R^{N\times 3}$ represent all points in the point-cloud with their three coordinates (x, y, z), and $A \in R^{N\times N}$ is the adjacency matrix describing connections between vertices. Each element $a_{ij} \in A$ can be either 1 or 0 if there is an edge between vertex i and j or not respectively.

3.2. Defining a Graph Convolutional Layer

Taking inspiration from [8], we defined a Graph Convolution Layer to be embedded into a Deep Multi-Layer Neural Network architecture. The Graph Convolution Layer can be defined in tensor notation [11] as:

$$GraphConv(C) = (A \times_1 V^T)_{(2)} H^T_{(3)} + b \tag{2}$$

where V and A are the vertices and adjacency matrix of G, $H \in R^{3\times C}$ is the total graph filter tensor with 3 representing the three-coordinates, $b \in R^C$ is the bias with parameter C representing the number of filters.

Given equation (2), all elements of H and b can be learned through a back-propagation technique. It is also possible to concatenate multiple layers of $GraphConv$ between themselves and other more “standard” deep neural networks layers like ReLU and Max Pooling.

3.3. The Siamese Ballistics Neural Network

The proposed Siamese Ballistic Neural Network consists of a couple of two identical neural networks with: an input layer, a 3 GraphConv layers with max pooling layers in-between, three fully connected layers, as well as an output layer on which the L is computed.

While the goal of simple CNNs is to learn a hierarchy of feature representations, Siamese Neural Network can be exploited for weakly supervised metric learning tasks. Instead of taking single sample as input, the network takes a pair of samples, and the loss functions are usually defined over pairs. A typical loss function of a pair has the following form:

$$L(s_1, s_2, y) = (1 - y)\alpha D_w^2 + y\beta e^{\gamma D_w} \tag{3}$$

where s_1 and s_2 are two pair cartridge samples, $y \in 0, 1$ is the similarity label, and D_w is a distance function defined as in [12]. We defined $\alpha = 1/C_p$, $\beta = C_n$ and $\gamma = -2.77/C_n$ where $C_p = 0.2$ and $C_n = 10$.

Unlike methods that assign binary similarity labels to pairs, the network aims at bring the output feature vectors closer for input pairs of the training labeled as similar, or push the feature vectors away if the input pairs are labeled as dissimilar. Figure 3 shows the SBNN architecture in detail.

3.4. Training and dataset augmentation

One of the most important step in every ballistic technique is the alignment phase. Many state-of-the-art techniques achieve the alignment with manual processing.

The proposed technique need to be trained in order overcome this problem. This is done by augmenting the dataset in such a way that for each sample, at training time, n copies of the input are created, by rotating among all the axis. Given that all point-clouds of the NBTRD dataset present rotations w.r.t X or Y axis, we have taken into account only rotations along the Z axis (that is 2D orations on X-Y plane). In our experiments, n is equal to 36 (each copy is the original one rotated by a step of 10 degree).

To make sure we generate reasonable proportion of similar and dissimilar pairs for the Siamese network, for each batch, we random select 100 samples from the same gun (matched pairs) and 900 from others (unmatched pairs). Hence batch size was 1000.

4. RESULTS

In a first set of experiments the goal is to recognize the model of the gun. Then we identified of the specific gun which fired a cartridge (gun identification), that is the most important information for scientific ballistic investigations. The technique described in this paper was trained and tested on the NBTRD dataset. We downloaded all available 3D point-clouds of cartridges of 9mm caliber. The samples are related to different gun brands and models.

We tuned hyper-parameters on a training set built by splitting the dataset into 70% of samples for training and 30% for test. Retrieval tests have been accomplished in order to evaluate the effectiveness of the proposed technique. For each class a single point-cloud has been randomly selected as query and the remaining ones as samples to be used to perform the retrieval test. The retrieval performance has been evaluated with the probability of the successful retrieval $P(n)$ in a number of test queries:

$$P(n) = \frac{Q_n}{Q} \tag{4}$$

where Q_n is the number of successful queries according to top n criterion, i.e., the correct classification is among the first n retrieved point-clouds, and Q is the total number of queries.

The average of $P(n)$ values with respect to all queries is reported in Figure 4. Results show that the proposed solution achieves a good margin of performances with respect to both tasks: gun and model identification. To further evaluate the proposed solution w.r.t. state-of-the-art methods we reproduced the Top-10-List for the gun identification test. This

Methodology	8	7	6	5	4	3	2	1	0
NIBIN [4]	13	25	23	19	13	9	5	1	0
[13, 6]	58	19	14	10	2	2	1	2	0
Tai et al.[5]	68	21	7	1	4	3	2	2	0
Banno et al.[2]	101	7	0	0	0	0	0	0	0
SBNN (our)	**108**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**

Table 1. Comparison of state-of-the-art techniques on TOP-10 list test. The proposed techniques is able to always find in the top 8 most similar samples of the correct cartridge.

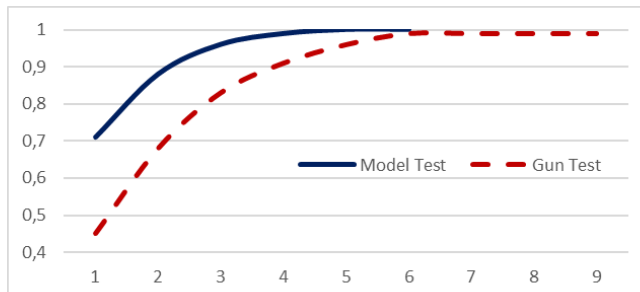

Fig. 4. Retrieval performance evaluation. The proposed approach achieves good performances for the retrieval task. Also gun retrieval tasks are good w.r.t. NBTRD dataset despite it does not contain a balanced distribution of samples among classes and models.

test is similar to the retrieval test described before, but conducted on a subset of the dataset built as follows: 108 samples were selected from the test set, with only 3 brands (Ruger, Sig Sauer, and Smith & Wesson brands), 36 samples for each brand, 9 cartridge samples for each specific gun. Therefore, the maximum number of positive matches for the Top-10-List test, will be 8 because 1 of the 9 cartridge cases for each specific gun is used as a query and therefore at most only 8 positive matches will appear in the test. Results of the Top-10-list Test w.r.t. state-of-the-art are shown on Table 1. Our method achieves the best results.

5. CONCLUSIONS AND FUTURE WORKS

In this paper a fully automated Forensic Ballistics comparison technique for cartridges was presented. The proposed Siamese Ballistics Neural Network was designed trained, and tested considering the NBTRD dataset. Results demonstrated the power of the techniques. Further investigations could be performed in order to understand what the hidden layers learn and if it is possible to exploit those features for the alignment task to enable visual inspection and better reporting.

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