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A correlation based bullet identification method using empirical mode decomposition

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ABSTRACT

The striations on bullet surface are 3D micro structures formed when a bullet is forcing its way out of barrel. Each barrel leaves individual striation patterns on bullets. Hence, the striation information of bullets is helpful for firearm identification. Common automatic identification methods process these images using linear time invariant (LTI) filters based on correlation. These methods do not consider the sensitivity of correlation based comparisons to nonlinear baseline drifts. The striations are undeniably random unique micro structures caused by random non-model-based imperfections in the tools used in rifling process, therefore any characteristic profile that is extracted from a bullet image is statistically non-stationary. Due to limitations of LTI filters, using them in smoothing bullet images and profiles may cause information loss and impact the process of identification. To address these problems, in this article, we consider bullet images as nonlinear non-stationary processes and propose a novel method which uses ensemble empirical mode decomposition (EEMD) as a preprocessing algorithm for smoothing and feature extraction. The features extracted by EEMD algorithm not only contain less noise, but also have no nonlinear baseline drifts. These improvements help the correlation based comparison methods to perform more robustly and efficiently. The experiments showed that our proposed method attained better results compared with two common methods in the field of automatic bullet identification.

1. Introduction

In this section, first we briefly review some earlier works in the field of automatic bullet identification. The last part of this section provides the theories and equations of empirical mode decomposition (EMD) and ensemble empirical mode decomposition (EEMD).

1.1. Automatic firearms identification using bullet signatures

The forensic firearm and tool mark identification as a field of forensic science has a history of more than one hundred years [1]. When a cartridge is fired from a firearm, specific marks are left on the bullet surface. Due to imperfections in manufacturing process of barrels, these marks have unique patterns for each rifled bore firearm. This is a key concept in the field of firearm identification. The characteristic features on bullet surfaces are divided into two groups: 1- class characteristics such as Number, width and Angle of land engraved areas (LEA) which are the same for all samples for a unique type of firearm (for example all AK-47 samples from the same manufacturer) 2- individual characteristics such as striation patterns, or abraded areas which are unique for each firearm and essential to find the relation between a bullet and a firearm. Traditional (visual) comparison of striations on fired bullets is an approach that is accomplished by a well-trained examiner using comparison microscope [2] or other visual comparison devices, however traditional comparisons may be time consuming. The development of computer-based automatic comparison systems is a solution to save time expenses in the traditional comparison procedures. These systems help experienced examiners to save their time and energy and in addition they can help inexperienced ones to make more rational decisions. Computer-aided systems such as Integrated Ballistics Identification System (IBIS) have been widely used in forensic laboratories since 1990 around the world [3–9]. These systems usually comprise of two main blocks: a data acquisition block and a feature/signature comparison block. The data acquisition block acquires high quality images from bullet surfaces under controlled illumination conditions. The feature/signature comparison block provides, through an algorithm, a signature representing the surface of the bullet and compares them with a relevant database using a certain similarity metrics. Based on these metrics, each bullet receives a similarity rank in the

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database. The ordered list of most promising matches provides a clearer vision for firearm examiner to decide whether the compared bullets match the subject bullet or not. Striations on bullet surface are often a set of straight lines with a certain angle to horizontal line. This twist angle is caused by circular rifling of barrels and varies between different firearm types and brands. To automate the bullet comparison procedure, several approaches used striation patterns as distinctive features [10–16]. Earlier methods used 2D images [10,11] while more recent studies are based on 3D measurements [12–16]. In 2D based methods usually, the first step includes rotating 2D bullet images such that mainstriations became perpendicular to horizontal line. Then, the bullet images were smoothed and averaged column wise to extract the 1-D averaged profiles. These profiles were then compared and ranked using cross-correlation metric [3,6,11,10,13]. The main difference between these methods lies within the preprocessing step. León et al. used an LTI Gaussian high-pass filter to homogenize 2D bullet images and top-hat morphologic transform to extract the signatures from averaged image profiles [11]. Chu et al. implemented an LTI Gaussian band-pass filter to smooth topography images and implemented a correlation-based strategy to select areas containing valuable striae information [10]. In Ref. [13] the same LTI filtering method and correlation-based strategy was applied but in order to select valid areas, a parameter named “striation density” was used to evaluate the areas to be averaged. Although the preprocessing steps in Ref. [14] is similar to Ref. [13] but the profile comparison is done using consecutively matching striae (CMS) criteria on topography measurements [17]. The reason behind these preprocessing procedures is the cross-correlation high sensitivity to noise and baseline drifts caused by averaging blank areas that have no striae information. The nature of bullet images itself (existence of random unique patterns of striations) and the varying conditions in the process of imaging (such as illumination changes, etc.) make them statistically non-stationary. Therefore, averaged profiles from bullet images may have different statistical properties (mean, variance, etc.) along their samples. Moreover, LTI filtering frameworks are not suitable for non-stationary environments (such as bullet images) because they may attenuate valuable information along with noise [18]. In addition, cross-correlation metric is not suitable for non-stationary signals because they have different means along samples unless their nonlinear baseline drifts are removed.

To address these problems, in this article, we propose a novel method based on empirical mode decomposition (EMD) for bullet identification. First the twist angle of a bullet image is calculated using canny edge detector and Radon transform. The image is rotated so that all main striations have 90° angles. The rotated image is then averaged column wise. The resultant average profile is decomposed using ensemble empirical mode decomposition (EEMD). By choosing appropriate decomposition modes, a de-noised profile is extracted from averaged profile which contains only striation information and no baseline drift. We compare these de-noised profiles using cross-correlation as a similarity metric and achieved 70.49% success rate for a hit list of 10%.

This article is organized as follows: following sub-section provides information about the EMD and EEMD algorithm. In Section 2 we explain our proposed method for automatic bullet identification and Section 3 demonstrates the implementation results of the proposed algorithm.

1.2. EMD and EEMD algorithm

The empirical mode decomposition (EMD) is a time-frequency decomposition method that was first introduced by Huang et al. in Ref. [19]. It is a nonlinear and non-stationary time domain decomposition technique. It is a data-driven algorithm that adaptively decomposes a signal into multiple scales or empirical modes, known as intrinsic mode functions (IMFs). Each IMF characterizes a certain narrow band amplitude-frequency modulation that is often linked with a particular statistical or physical process. An IMF must satisfy two conditions [19]:

1- The number of local extrema and the number of zero crossing points must be either equal or at most differ by one.

2- The mean of its upper and lower envelopes equals zero.

EMD decomposes a given signal $x(t)$ into a series of intrinsic mode functions (IMFs) which are extracted via an iterative sifting process. First, the local extrema of the signal are found and connected by cubic splines to form the upper/lower envelopes. The average of the two envelopes is then subtracted from the original signal. This sifting process is done repetitively for several times to acquire the first IMF. Subsequently, the first IMF is subtracted from the original signal to obtain the residual. The residual is considered as the input for the aforementioned procedures. In turn, subsequent IMFs with lower oscillation frequencies are derived using the same process and the newly obtained residue. The sifting process in EMD algorithm can be expressed in the following steps [19]:

1- Detect all local maxima and minima of signal $x(t)$.

2- Obtain upper envelope by connecting local maxima using cubic splines. Obtain lower envelope of signal $x(t)$ by connecting local minima using cubic splines. Subtract the average of these two envelopes (m_{10}) to from signal x to obtain the candidate for first IMF (h_{10}) see Fig. 1:

$$x(t) - m_{10}(t) = h_{10}(t) \tag{1}$$

Ideally, $h_{10}(t)$ is an IMF, If it is not, steps 1 to 2 are repeated over and over (sifting). In each iteration of the sifting process, the resulting $h_{10}(t)$ is treated as the original signal ($x(t)$) for the next iteration.

In other words, the equation below is repeated for a predefined number of iterations (k) until it satisfies the two aforesaid conditions of IMF:

$$h_{1(k-1)} - m_{1k} = h_{1k} \tag{2}$$

There are some criteria for terminating the sifting process. A commonly used one is the Standard Deviation (SD):

$$SD = \sum_{t=0}^{T} \frac{|h_{1(k-1)}(t) - h_{1k}(t)|^2}{h_{1(k-1)}^2(t)} \tag{3}$$

The value of termination SD is usually selected in the range [0.2, 0.3].

3- Once the first IMF $c_1(t)$, is obtained, obtain the residue:

$$r(t) = x(t) - c_1(t) \tag{4}$$

4- Treat the residue $r(t)$ as the original signal and do the steps 1 to 4 to acquire additional IMFs.

5- Repeat step 1 to 4 to obtain IMFs until the residue of signal in step 5 has no more than 3 extrema.

We can reconstruct the signal $x(t)$ using a linear summation of IMFs and residue i.e.:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{5}$$

Where n is the number of IMFs, $c_i(t)$ and $r_n(t)$ are the i^{th} IMF and nth residue respectively.

As an improved version of EMD, EEMD (Ensemble Empirical Mode Decomposition) was originally proposed to resolve the mode-mixing problem. In this method, white noise is added to the