

Literature Review

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As the need for computationally-intensive methods to analyze forensic data has grown, so too has the need for user-friendly tools to experiment with and improve upon these methods. In this work, we discuss developments to a particular class of algorithms used to compare cartridge case evidence known as the Congruent Matching Cells (CMC) method. Chapter [#] discusses a modularization of the algorithm into a “pipeline” that enables reproducibility, experimentation, and comprehension. Chapter [#] introduces novel pieces of this pipeline that we demonstrate provide improvements to the current state-of-the-art. Chapter [#] details a suite of diagnostic tools that illuminate the inner-workings of the algorithm and help determine when and why the algorithm does or does not “work” correctly.

Forensic Examinations

A primary goal of a forensic examination is to determine the source of a piece of evidence. This is referred to as the *source identification* problem [Ommen and Saunders, 2018]. A common setting for source identification problems involves obtaining evidence of unknown source from a crime scene and either evidence from a known source or other evidence of unknown source. For example, a bullet found at a crime scene may be compared to a suspect’s firearm. Such evidence is sent to a forensic lab where a trained Firearms and Toolmarks examiner compares the “questioned” bullet to bullets fired from the suspect’s firearm to determine whether the suspect’s firearm was the original source. In this work, we develop a method to supplement such an examination by providing an objective measure of similarity between the two pieces of evidence.

Pattern Evidence

Firearms and Toolmarks Analysis

The Firing Process

Cartridge Case Impressions

Firearms and toolmarks (F&T) examination involves studying markings or impressions left by a firearm or other tool (e.g., a screwdriver) on a surface [Thompson, 2017]. The focus of this work is on a subset of F&T problems that deal with the comparison of cartridge case evidence. A *cartridge case* is the part of firearm ammunition that encases a projectile (e.g., bullet, shot, or slug) along with the explosive used to propel the projectile through the firearm. When a firearm is discharged, the projectile is propelled down the barrel of the firearm, while the cartridge case is forced towards the back of the barrel. It strikes the back wall, known as the *breech face*, of the barrel with considerable force, thereby imprinting any markings on the breech face onto the cartridge case, creating the so-called *breech face impressions*. These markings have been suggested to be unique to a firearm and are used in forensic examinations to determine whether two cartridge cases have been fired by the same firearm.

During a forensic examination, two pieces of ballistic evidence are placed under a comparison microscope. Comparison microscopes allow for a side-by-side comparison of two objects within the same viewfinder, as seen in Figure 1. A pair of breech face images is aligned along the thin black line in the middle of the images. The degree to which these breech face markings can be aligned is used to determine whether the two cartridge cases came from the same source; i.e., were fired from the same firearm. These breech face impressions are considered to be a firearm’s unique “fingerprint” left on a cartridge case [Thompson, 2017].

A F&T examination typically ends in one of three conclusions: identification, meaning the evidence originated from the same source, exclusion, meaning the evidence did not originate from the same source, or inconclusive, meaning there is insufficient information to conclude identification or exclusion [AFTE Criteria for Identification Committee, 1992]. Examiners rarely need to provide quantitative justification for their conclusion. Even for qualitative justifications, it can be difficult to determine what the examiner is actually “looking at” to arrive at their conclusion [Ulery et al., 2014]. For cartridge case comparisons, similarity between the breech face impressions of two cartridge cases, among other factors, is used by the examiner to make their determination.

Due to the opacity in the decision-making process, examiners have been referred to as “black boxes” in a similar sense to black box algorithms [OSAC Human Factors Committee, 2020]. Their evidentiary conclusions are fundamentally subjective, and there is empirical evidence to suggest that conclusions differ across examiners when presented with the same evidence and even within a single examiner when presented with the same evidence on two different occasions [Ulery et al., 2011, 2012]. This suggests the need to supplement these black box decisions with transparent, objective techniques that quantitatively measure the similarity between

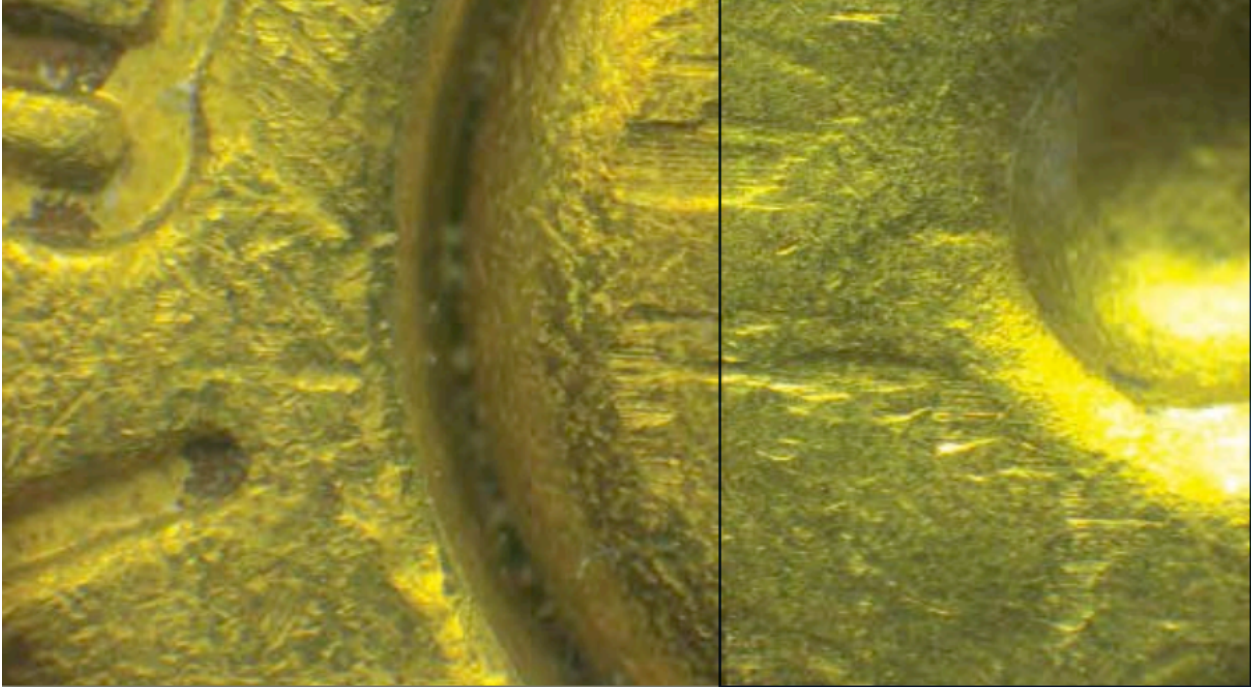


Figure 1: A cartridge case pair with visible breech face impressions under a microscope. A thin line can be seen separating the two views. The degree to which the markings coincide is used to conclude whether the pair comes from the same source.

pieces of evidence [National Research Council, 2009, President’s Council of Advisors on Sci. & Tech., 2016].

In this work, we focus on a specific set of techniques used to compare cartridge case evidence.

Forensic Comparison Pipelines

Recent work in many forensic disciplines has focused on the development of algorithms to measure the similarity between pieces of evidence including glass [Curran et al., 2000, Park and Tyner, 2019, Tyner et al., 2019], handwriting [Crawford, 2020], shoe prints [Park and Carriquiry, 2020], ballistics [Hare et al., 2017, Tai and Eddy, 2018], and toolmarks [Hadler and Morris, 2017, Krishnan and Hofmann, 2018]. These algorithms often result in a numerical, non-binary (dis)similarity score for two pieces of evidence. A non-binary score adds more nuance to an evidentiary conclusion beyond simply stating whether the evidence did or did not originate from the same source as would be the case in binary classification. For example, the larger the similarity score, the “more similar” the evidence. However, a binary (or ternary, if admitting inconclusives) conclusion must ultimately be reached by an examiner. Whether a decision should be reached based solely on results of a comparison algorithm (e.g., defining a score-based decision boundary) or if an examiner should incorporate the similarity score into their own decision-making process is still up for debate [Swofford and Champod, 2021]. In this work, we view forensic comparison algorithms as a supplement to, rather than a

replacement of, the forensic examination.

We conceptualize forensic comparison algorithms as evidence-to-classification “pipelines.” Broadly, the steps of the pipeline include:

1. capturing a digital representation of the evidence,
2. pre-processing this representation to isolate or emphasize a region of interest of the evidence,
3. comparing regions of interest from two different pieces of evidence to obtain a (perhaps high-dimensional) set of similarity features,
4. combining these features into a low-dimensional set of similarity scores, and
5. defining a classification rule based on these similarity features.

This is similar to the structure discussed in [Rice \[2020\]](#). We add to this structure the emphasis that each step of the pipeline can be further broken-down into modularized pieces. For example, the pre-processing step may include multiple sub-procedures to isolate a region of interest of the evidence. [Figure 2](#) shows three possible variations of the cartridge case comparison pipeline as well as the parameters requiring manual specification and alternative modules. The benefits of this modularization include easing the process of experimenting with different parameters/sub-procedures and improving the comprehensibility of the pipeline.

In the following sections, we detail recent advances to each of the five steps in the pipeline outlined above. We narrow our focus to advances made in comparing F&T evidence.

Digital Representations of Cartridge Case Evidence

Digital representations of cartridge case evidence commonly come in one of two modes: 2D optical images or 3D topographic scans. A common way to take 2D optical images is to take a picture of the cartridge case under a microscope. This implies that the digital representation of the cartridge case surface is dependent on the lighting conditions under which the picture was taken. Some recent work has focused on comparing 2D optical images [[Tai and Eddy, 2018](#), [Tong et al., 2014](#)], although the use of 3D microscopes has become more prevalent to capture the surface of ballistics evidence.

Using a 3D microscope, we obtain scans at the micron (or micrometer) level that are more light-agnostic than a 2D image [[Weller et al., 2012](#)]. One common 3D scanning procedure is disc scanning confocal microscopy. This procedure works by shining a focused beam of light on the cartridge case surface. This light is reflected back onto a pinhole allowing a limited height range to pass through. The microscope scans through different

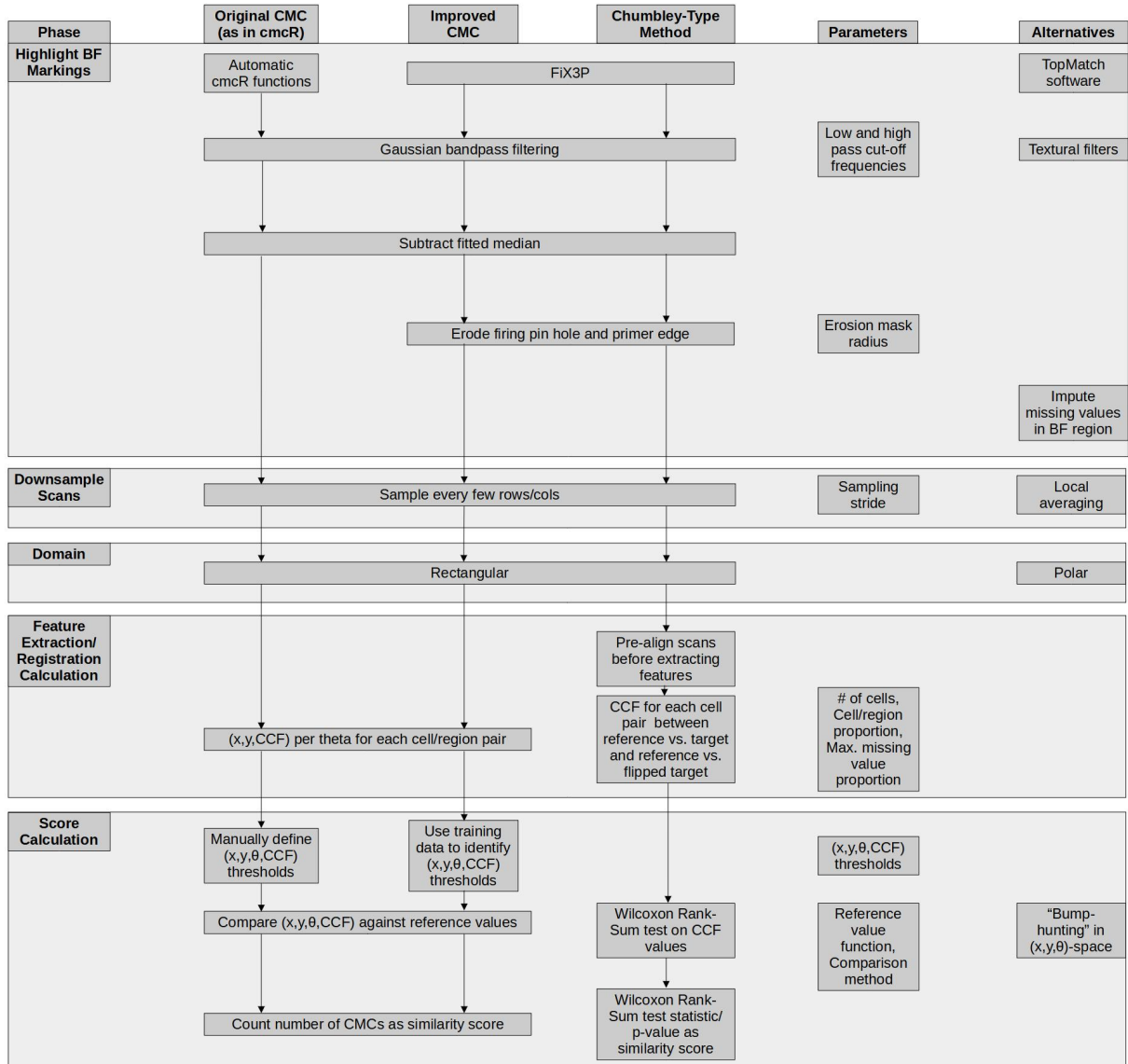


Figure 2: Variations upon the cartridge case comparison pipeline. The first three columns detail the pipeline with different sub-procedures. The fourth column shows the parameters that require manual specification at each step. The fifth column shows alternative processing steps that could replace steps in the existing pipeline.

height range “slices” and compiles all these slices into a single 3D topography of the cartridge case primer surface. Figure 3 shows a 2D image and 3D topography of the same cartridge case primer.

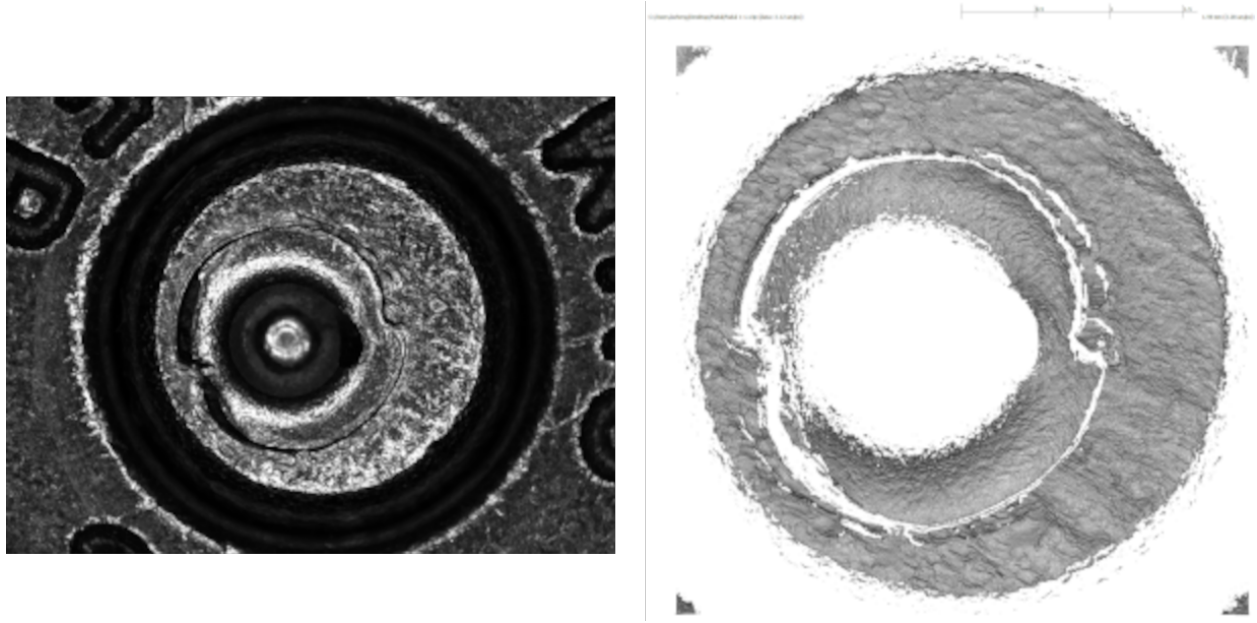


Figure 3: A cartridge case from Fadul et al. [2011] captured using 2D confocal reflectance microscopy (left) and 3D disc scanning confocal microscopy (right).

More recently, Cadre Forensics™ introduced the TopMatch-3D High-Capacity Scanner [Weller et al., 2015]. This scanner collects images under various lighting conditions of a gel pad into which the cartridge case surface is impressed and combines these images into a regular 2D array called a *surface matrix*. The physical dimensions of these objects are about 5.5 mm^2 captured at a resolution of 1.84 microns per pixel (1000 microns equals 1 mm).

When applied to ballistics evidence, these 3D scans are commonly stored in the ISO standard x3p file format [ISO 25178-72, 2017]. x3p is a container consisting of a single surface matrix representing the height value of the surface and metadata concerning the parameters under which the scan was taken (including size, resolution, creator, etc.). It has been empirically demonstrated that comparing 3D topographic scans of cartridge case evidence leads to more accurate conclusions compared to comparing 2D optical images of the same evidence [Tai, 2019, Tong et al., 2014, Song et al., 2014].

Pre-processing Procedures for Cartridge Case Data

When capturing the surface of a cartridge case, the result is bound to contain extraneous regions due to the incongruity between the circular primer and the rectangular array in which the surface data are stored. Figure 3 shows an example of a 2D image and 3D scan of the same cartridge case. We can see, for example,

that the corners of these arrays include non-primer regions of the cartridge case surface. Additionally, the center of the cartridge case primer features an impression left by the firing pin during the firing process. In most applications, impressions left by the firing pin are compared separately from the breech face impressions [Zhang et al., 2016] [cite others?]. As the focus of this work is on the comparison of breech face impressions between two cartridge cases, only the annular region surrounding the firing pin impression is of interest. The annular breech face impression region must be segmented away from the rest of the captured surface.

Both the 2D optical and 3D topographic representations of cartridge case surfaces are fundamentally pictorial in nature. As such, many image processing and computer vision techniques are used to automatically isolate the breech face impression region. Tai and Eddy [2018] uses a combination of histogram equalization, Canny edge detection, and morphological operations to isolate the breech face impressions in 2D images. Various types of Gaussian filters are commonly employed to remove unwanted structure. Tong et al. [2014] uses a low-pass Gaussian filter that removes noise via a Gaussian-weighted moving average operation. Chu et al. [2013], Song et al. [2018] use a bandpass Gaussian filter, which simultaneously performs the function of a low-pass filter along with a high-pass filter to remove global structure from the scan. Other versions of the bandpass filter are used in Song et al. [2014], Chen et al. [2017], Ott et al. [2017] that accomplish tasks such as omitting outlier surface values or addressing boundary effects [ISO 16610-71, 2014, Brinkman and Bodschwinn, 2003].

Instead of using automatic procedures, others have used subjective human intervention to isolate the breech face impressions. For example, [Song et al., 2018] indicate that cartridge cases are “manually trimming to extract the breech face impression of interest.” In Roth et al. [2015], examiners manually identify the borders of the breech face impression region by placing points around an image of the cartridge case primer.

Figure 4 illustrates a sequence of pre-processing procedures applied to a cartridge case surface. By breaking the broader pre-processing step into modularized pieces, we can easily devise other arrangements of these pre-processing procedures that may improve the segmenting or emphasizing of the breech face impressions. Experimentation is enabled by the modularity of the pipeline.

Cartridge Case Evidence Feature Extraction

After applying the pre-processing procedures to two cartridge case scans, their breech face impressions are compared and similarity features are extracted. Given that the cartridge cases at this point are represented as high-dimensional matrices, this can be thought of as a dimensionality reduction of the high-dimensional surface arrays to a set of similarity statistics.

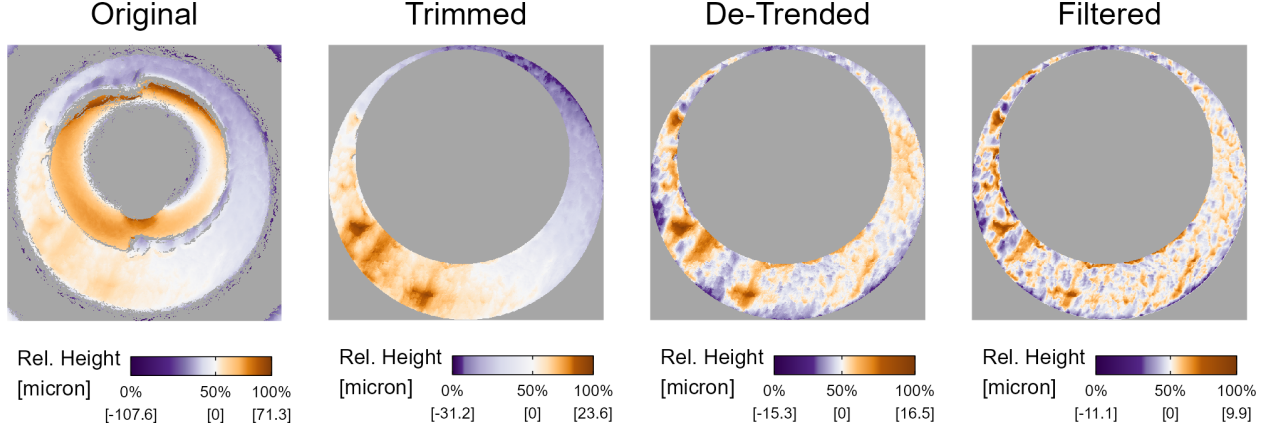


Figure 4: A cartridge case undergoing various pre-processing steps. Note that the distribution of height values changes from left to right as more extraneous noise is removed from the scan.

A variety of features have been proposed to quantify the similarity between two cartridge case surface arrays. [Tai and Eddy \[2018\]](#) propose calculating the cross-correlation function (CCF) value between two cartridge cases across a grid of rotations. It is assumed that the CCF will be larger around the “true” rotation for matching cartridge case pairs than for non-matching pairs. [Riva and Champod \[2014\]](#) proposed combining the CCF between the two aligned scans with the element-wise median Euclidean distance and median difference between the normal vectors at each point of the surface. Later, [Riva et al. \[2016, 2020\]](#) applied Principal Component Analysis to reduce these three features down to two principal components onto which a 2D Kernel Density Estimator could be fit.

Pertinent to this work is the cell-based comparison procedure originally outlined in [Song \[2013\]](#). The underlying assumption of [Song \[2013\]](#) is similar to that of [Tai and Eddy \[2018\]](#): that two matching cartridge cases will exhibit higher similarity when they are “close” to being correctly aligned. While [Tai and Eddy \[2018\]](#) measured similarity using the CCF between the two full scans, [Song \[2013\]](#) proposes partitioning the scans into a grid of “correlation cells” and counting the number of similar cells between the two scans. The rationale behind this procedure is that many cartridge case scans have regions that do not contain discriminatory markings. As such, comparing full scans may result in a lower correlation than if one were to focus on the highly-discriminatory regions. Dividing the scans into cells allows for the identification of these regions.

After breaking a scan into a grid of cells, each cell is compared to the other scan to identify the rotation and translation, known together as the *registration*, at which the cross-correlation is maximized. [Song \[2013\]](#) assume that the cells from a truly matching pair of cartridge cases will “agree” on their registration in the other scan. Details of this procedure are provided in [Chapter].

Similarity Scores for Cartridge Case Evidence

Following feature extraction, the dimensionality of these features is further reduced to a low-dimensional, usually univariate, similarity score.

After calculating the CCF across various possible registrations, [Tai and Eddy \[2018\]](#) propose using the maximum observed CCF value as the univariate similarity score. In this case, a binary classification can be achieved by setting a CCF threshold above which pairs are classified as “matches” and below which as “non-matches.” [Tai \[2019\]](#) proposes setting a CCF cut-off that maximizes the precision and recall in a training set of pairwise comparisons.

[Riva et al. \[2016, 2020\]](#) use a training set to fit two 2D kernel density estimates to a set of features from matching and non-matching comparisons. Using these estimates, they are able to estimate the score-based likelihood ratio (SLR) for a new set of features. This SLR can be viewed as a similarity score [[Garton et al., 2020](#)].

In the case of the cell-based comparison procedure discussed above, the total number of cells that are deemed “congruent matching” is used as a similarity score. The criteria used to define “congruent matching” has changed across papers [[Song et al., 2014](#), [Tong et al., 2014, 2015](#), [Chen et al., 2017](#)] and will be discussed in greater detail in [Chapter]. The authors of these papers have consistently used a decision boundary of six “Congruent Matching Cells” to distinguish matches from non-matches.

[Zhang et al. \[2020\]](#) applies the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [[Ester et al., 1996](#)] to the features from the cell-based comparison procedure to determine if any clusters form amongst the per-cell estimated registration values. This is based on the assumption that any cells that come to a consensus on their registration should form a cluster in translation (x, y) and rotation θ space. [Zhang et al. \[2020\]](#) proposes a binary classifier based on whether any clusters are identified by the DBSCAN algorithm. If a cluster is found for a particular pairwise comparison, then that pair is classified as a “match” and otherwise as a “non-match.”

Reproducibility of Comparison Pipelines

[Discuss concepts related to reproducibility and repeatability in science (cite problems related to reproducibility), then narrow to algorithms (cite computational reproducibility papers), then narrow to forensic comparison algorithms, then end with how modularization enables reproducibility of forensic comparison algorithms.]

Visual Diagnostics

Forensic examiners often provide expert testimony in court cases. As part of this testimony, an examiner is allowed to not only provide facts about the outcome of a forensic examination, but also their opinion about what the results mean. A party to a court may challenge the examiner on the validity of the underlying scientific method or whether they interpreted the results correctly [American Academy of Forensic Sciences, 2021]. In these situations, examiners need to be able to explain the process by which they reached an evidentiary conclusion to the fact finders of the case; namely, the judge or jury. As algorithms are more often used in forensic examinations, the technical knowledge required to understand and explain an algorithm to lay-people has increased. While in some cases the authors of the algorithm have been willing to provide testimony to establish the validity of the algorithm [Indiana County Court of Common Pleas, 2009], this will become less viable as algorithms become more prevalent. Indeed, even the most elegant improvements to an algorithm may be moot if an examiner can’t explain the improvements in their testimony.

The resources required to educate examiners on the use of highly technical algorithms makes additional training seem currently implausible. An alternative is to develop algorithms from the ground-up to be intuitive for examiners to understand and explain to others. *Explainability* refers to the ability to identify the factors that contributed to the results of an algorithm [Belle and Papantonis, 2021]. For example, understanding “why” a classifier predicted one class over another.

Myriad techniques exist to explain the results of an algorithm. These range from identifying instances of the training set that illuminate how the model operates [Deng, 2018] to fitting more transparent models that approximate the complex model accurately [Puiutta and Veith, 2020] to explaining the behavior of the algorithm in a small region of interest [Ribeiro et al., 2016, Goode and Hofmann, 2021]. Many of these methods require additional technical knowledge to interpret these explanations.

A less technical approach is to use visualizations that facilitate understanding of model behavior. Properly constructed visuals enable both exploratory data analysis and diagnostics [Buja et al., 2009]. Given that many of the procedures by which cartridge case evidence is captured, processed, and compared are based on image processing techniques, a visual diagnostic is an intuitive mode of explanation for experts and lay-people alike. In this work, we develop a suite of visual diagnostic tools that can be used to explain the behavior of the cartridge case comparison pipeline.

Improving the Cartridge Case Analysis Pipeline

Morphological Transformations

Density-Based Spatial Clustering of Applications with Noise

Features Based on Visual Diagnostics

Much of the literature on “explainable” algorithms are focused on black-box machine learning algorithms such as Random Forests or Multi-layer Neural Networks. [More to say here?] Less focused is placed on constructing explainable features. Feature selection and engineering is a critical, often time-intensive step in the data analysis process that isn’t often

We use the visual diagnostic tools discussed in Chapter [5] to develop a set of features. By definition, these features are human-interpretable unlike, for example, features that are calculated in the convolution layer of a convolutional neural network. The interpretability of these features imply that they can be explained to forensic examiners or lay-people. This will make it easier to introduce such methods into forensic labs and court rooms.

Implementation Considerations

This cartridge case comparison pipeline is similar to other data analysis pipelines. Much like other data analysis pipelines, the procedural details can be obscured as the goals of the analysis become more sophisticated. This is helpful neither for the individual performing the analysis nor for any consumer of the results. As such, it is worthwhile to design tools that make the data analysis procedure easier to implement and understand [Wickham, 2014].

Beyond simply conceptualizing the cartridge case comparison procedure as a pipeline, we also implement the procedure as a sequence of algorithms that can programatically be connected together. In particular, we utilize the pipe operator `%>%` available from the `magrittr` R package [Bache and Wickham, 2022]. This operator allows the output of one function to be passed as input to another without assigning a new variable. Data can be incrementally transformed as they move from one function to another.

Implementing a data analysis procedure using the pipe operator allows the user to think intuitively in terms of verbs applied to the data. Table 1 illustrates two examples of pipelines that utilize the pipe operator. The left-hand example shows how an R data frame can be manipulated using functions from the `dplyr` package. Functions like `group_by`, `summarize`, and `filter` are simple building blocks that can be strung together to create complicated workflows. The right-hand example similarly illustrates a cartridge case object passing through the comparison pipeline. While the full comparison procedure is complex, the modularization to the

`preProcess_`, `comparison_`, and `decision_` steps, which can further be broken-down into simple building blocks, renders the process more understandable to, and flexible for, the user.

Data Frame Manipulation Example	Cartridge Case Comparison Example
<code>dataFrame %>%</code> <code> group_by(category) %>%</code> <code> summarize(x = summary(var)) %>%</code> <code> filter(x > 0) ...</code>	<code>cartridgeCase1 %>%</code> <code> preProcess_func(params1) %>%</code> <code> comparison_func(cartridgeCase2,</code> <code> params2) %>%</code> <code> decision_func(params3) ...</code>

Table 1: Two examples of data analysis workflows that utilize the pipe operator. The left side shows a data frame manipulation while the right side shows a comparison of two cartridge cases.

Our implementation is structured to adhere to the “tidy” principles of design [Wickham et al., 2019]. The `tidyverse` is a collection of R packages that share an underlying design philosophy and structure. The four principles of a tidy API are:

1. Reuse existing data structures.
2. Compose simple functions with the pipe.
3. Embrace functional programming.
4. Design for humans.

Adherence to these principles makes it easier to engage with and understand the overall data analysis pipeline. In our application it also enables experimentation by making it easy to change one step of the pipeline and measure the downstream effects [Zimmerman et al., 2019]. Each step of the cartridge case comparison pipeline requires the user to define parameters. These can range from minor, such as the standard deviation used in a Gaussian filter, to substantial, such as choosing the algorithm used to calculate the similarity score. So far, there is no consensus on the “best” parameter settings. A large amount of experimentation is yet required to establish these parameters. A tidy implementation of the cartridge case comparison pipeline allows more people to engage in the validation and improvement of the procedure.

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