

Indian Journal of Modern Research and Reviews

This Journal is a member of the 'Committee on Publication Ethics'

Online ISSN:2584-184X



Research Article

Detection of Signature Forgery Using Morphological Features: A Review of Structural Characteristics and Statistical Approaches

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DOI: <https://doi.org/10.5281/zenodo.22844552>

Abstract

The traditional role of handwritten signatures has been in uniquely identify, authorise, and confirm transactions within financial, legal, administrative and forensic domains. In an ever-increasing digitised world of data entry, disputed signatures are frequently incorporated into questioned document examination. Traditional forensic inspection methods rely on subjective evaluation of writing styles by experts, but modern analysis methods involve increasing quantification used to distinguish authenticated from forged signatures.

Among these quantitative analysis methods is morphologic analysis, a relatively straightforward method using measurable structural and geometric properties derived from images of signatures.

Various features associated with writing height, width, aspect ratio, area, perimeter, eccentricity, density of pixels, contour shape, distribution of pixels, stroke and structural elements and spatial relationships can provide a good indication of the morphology of signature. The article reviews the relevance of morphological features in handwritten signature forgery detection using offline signature verification as a focal theme. Information within the literature from geometric, structural, directional, graphometric, texture and machine learning approaches is reviewed. The use of statistical methodology in signature verification research is explored, including descriptivestatistics, hypothesis testing, Correlation Analysis, Principal Component Analysis, Fisher Linear Discriminant Analysis, Support Vector Machine (SVM), Neural Network (NN), and performance indices like Accuracy, False Acceptance Rate (FAR), False Rejection Rate (FRR) and Error Equality Rate (ERR).

Comparing key studies, it was revealedthat noneof the single features can authenticate a signature; usually, a combination of features yields effective distinction.

Key limiting factors such as the natural variation of a writer's signature (intra-writer variance), image acquisition condition variations, scarcity of forensic signature databases, possibility of high-skilled forgeries, class-imbalanced data, and lack of unified reporting standards for these analyses were considered. More importantly, it requires correlation of both interpretable morphologic values with rigorous statistical modelling, Explainable Artificial Intelligence, standard forensic datasets, and a forensic validation approach.

Manuscript Information

- ISSN No: 2584-184X
- Received: 08-08-2026
- Accepted: 16-09-2026
- Published: 19-09-2026
- MRR:4(9); 2026: 204-210
- ©2026, All Rights Reserved
- Plagiarism Checked: Yes
- Peer Review Process: Yes

How to Cite this Article

Negi M, Khanna J. Detection of Signature Forgery Using Morphological Features: A Review of Structural Characteristics and Statistical Approaches. Indian J Mod Res Rev. 2026;4(9):204-210.

Access this Article Online



www.mrrjournal.in

KEYWORDS: Handwritten signature; signature forgery; morphological features; offline signature verification; questioned documents; geometric features; statistical analysis; forensic document examination; image analysis; machine learning.

1. INTRODUCTION

A handwritten signature is a graphic representation uniquely drawn by an individual which asserts or attests the identity of an individual, indicates assent, approval or intention. Signatures appear on documents relevant for money transactions, contractual arrangements, legal deeds, identification documents, institutional papers, etc. that call for proof of authenticity. Consequently, the proof in whether the questioned signature in dispute is genuine or a fake is of tremendous forensic value.

Traditionally, examination of signatures is within the realm of questioned-document examination. A forensic document examiner will look for similarities and differences between a questioned signature and standards by determining the values or degree of several characteristics namely, quality of strokes, movement, proportionality, alignment, space between items, pen-lifts, connecting strokes, forming the letters, originating and final stroke formations, construction and composition. A signature verification is a comparative analysis that would need appropriate, representative samples. With the progress of digital image processing techniques, a growing number of studies are dealing with ways to encode characteristics of a signature as digital values.

Two main approaches used in signature verification are the dynamic and the static approaches. The dynamic approach captures signature production features dynamically like speed, acceleration, pressure as well as stroke-order and writing order. On the contrary, the static approach analyses only a post-writing digital image of the signature, thus it fails to capture dynamic features which are quite instrumental for a dynamic signature authentication, but because of the nature of questioned documents, static signatures were quite a relevant technique in the forensic scenario.

The earlier work on automatic signature verification proved that preprocess, feature extraction, comparison methods, and evaluation criteria play an important part. Plamondon and Lorette's review is outstanding to analyze both static and dynamic signature verification and the consideration between comparison methods and feature representations.

One of the rather interpretative methods within a static verification system of signatures are the techniques that follow morphological analysis. This treats the signature as an object, instead of simply a collection of pixels, and seeks to quantitatively measure its physical properties. Basic geometric features would represent the shape of the signature, like height, width, aspect ratio (also called calibre), and area whereas more structural properties may involve counting endpoints, loops, spacing, slope, density in various regions, character proportions, boundary shape, region information etc.

With the proliferation of machine learning techniques signature verification extended the use of handcrafted features of morphological types. They remain scientifically relevant as they are interpretable, require small computational effort, and their usage in discriminating the signature could be explained as to the disparity between the target signatures. Nevertheless, it has been proven that although deep learning has

outperformed these techniques in tests it appears that the question of robust static signature forgery is still to be fully solved as there exist similarities between legitimate signatures, thus very easily, proficient forgery would appear authentic too. The purpose of this review is to illustrate the morphological characteristic feature set of signatures which can be applied towards a signature forgery detection system, present some statistically and computationally based methods described in the literature, compare the respective strategies and point towards future directions and research needed for this forensic application.

2. LITERATURE REVIEW

2.1 Development of Signature Verification Research

Research in automated signature verification is now decades old. A common theme of the initial stages of research was extraction of measurable features in handwriting and signatures and comparison with queried signatures. Traditional techniques typically consist of hand-crafted features and then used some pattern-recognition or statistical methodology (statistical classifiers).

Plamondon & Lorette provided an excellent early survey of automatic signature verification and writer identification, distinguishing static and dynamic paradigms.

Features such as preprocessing stages, comparison process, and evaluation measures are typically present and were discussed extensively in the authors' overview. Later on most of the research appeared concerning offline signature verification where signatures are treated as an image. Hafemann et al. Provided a recent excellent review on this topic which discusses several of features extracted such as geometrical, graphometrical, directional, textured or other features that are handcrafted.

Within geometrical features, height, width, caliber (ratio between height and width), area, endpoints, closed loops were named by the authors as suitable for signature verification.

The next stage was those approaches where machine learning was used for classification. Support Vector Machines (SVM), Neural Networks (NN), Hidden Markov Models (HMM), k-NN, discriminant analysis and other classifiers were used for identification purposes distinguishing authentic and forgery signatures. Reviews were present discussing the feature selection and feature extraction importance in terms of the efficiency of the classification process.

A new stage was introduced with the application of deep learning. Hafemann et al. Successfully used Convolutional Neural Networks for the task, in which the feature representation was learned directly from images and significant improvement compared to existing offline recognition techniques were found on standard databases.

However, they also stated that skillful forgeries represented a great difficulty in offline verification context.

A systematic review Hameed et al., which analysed 56 papers published in the range of 2014-2019 found out that the amount of deep learning-based approaches have increased. In the

aforementioned review, many open issues regarding feature extraction and classification performance are described suggesting that the obtained performances on the standard data sets have been sometimes overestimated compared to real-world usage.

2.2 Genuine Signatures and Forged Signatures

One key issue in the signature forgery research is the fact that, when a real signature is produced, no writer generates precisely the same one on all occasions. The natural intra-writer variations are the result of variations in physical pose, writing speed, state of mind, tiredness, pen, paper, writing instruments, etc.

This is why no single rigid model represents a genuine signature; to produce a reliable verification system. The challenge is to distinguish between the natural variation of signatures written by a given writer and a systematic variation due to a different writer, i.e. a forgery.

Regarding forgery, the writer also has several forms: among them, we consider simple forgery, simulated forgery, traced forgery and skilled freehand forgery. The skilled forgeries pose a serious problem, as some may achieve to reproduce some of morphological characteristics of genuine signature while their subtle structure or dynamic characteristics are altered.

3. Morphological Features Used in Signature Analysis

Morphological features capture quantities that define the global shape, size, configuration and layout of a signature and they can be computed on a binarized or adequately segmented signature.

3.1 Signature Height

Signature Height refers to the vertical size in pixels. Height may be influenced by the writing size of a person. Height differences may result from: different styles of writing; image normalization; or simulation. Signature Height is not suitable for signatures authentication as, naturally, the same writer's signature will have different sizes.

3.2 Signature Width

Width is the horizontal measurement. Width can offer clues to how the author used his horizontal space, the relative size, or the signature in general. It may be an aspect that a forger could accurately imitate the look, yet get slightly different the dimensions of its horizontally.

3.3 Aspect Ratio

Aspect ratio is a relationship of width and height: $AR = W/H$. Aspect ratio is also called caliber in signature-verification literature. It presents a non-dimensional measure for the shape characteristic of a signature. It clearly separates a long-ish signature from a smallish signature.

3.4 Signature Area

This is the measure of the total space in the image taken up by the strokes that constitute the signature. For binary images a quick approximation can be made $A = P_i$, where P_i is

foreground pixels. This measure is related to both the height and width of the signature, but also to how densely the signature has been formed.

3.5 Perimeter

The perimeter is the distance around the signature boundary. The perimeter is an indicator of the complexity of the outline. A signature that is highly irregular or has a complex outline containing many loops will likely have a higher perimeter for a given area than one with a smooth, rounded boundary.

3.6 Compactness

There are two measures for compactness, where most people mean "compactness is simply given by $C = 4\pi A/P^2$ where A is area and P is perimeter". High value means the object is comparatively 'fat' or compact. Low value means the shape is elongated or irregular. As signatures are usually quite irregular and elongated in appearance, maybe it can be used to classify them.

3.7 Eccentricity

This measure specifies how long an object is in relation to an 'oval' shaped feature. A high value of eccentricity means that the object is very long, and a small value means it is compactly sized. This can be used in signature analysis as it tells us how organized the signature is in a directional sense, and may supplement aspect ratio.

3.8 Pixel Density

The pixel density can measure the percentage of the bounding region covered by pixels of the signature, which is $D = A/(WH)$. This feature could be useful to discriminate among signatures with thinly and largely-distributed strokes, and signatures with densely-written structures. The regional pixel density measurements can be obtained after dividing a signature by grid.

3.9 Structural Features

Morphological analysis may also include descriptions of the structures themselves. Number of connected components, number of endpoints, presence of loops, presence of intersecting strokes, skeleton length, number of junction points, orientation of strokes, above and below average height, alignment with the baseline, inner density, or distribution within the area can be described.

3.10 Graphometric Features

Graphometric characteristics are important at an intermediate level between traditional forensic analysis and computerized image analysis, and an example of these measures are, for example, proportions, alignment, slope of base line, distances, caliber, relative size and distribution of strokes.

4. Statistical Methods Used in Literature

4.1 Descriptive Statistics

Descriptive statistics are a typical initial step to conduct quantitative analysis. Mean, median, standard deviation, variance, minimum, maximum, range, inter quartile range and coefficient of variation are all important characteristics of data describing distribution shape. For a feature X, the arithmetic mean is described as and the standard deviation indicates how far away the data values are from the mean, measures. If used to present how the morphometrical values of a real signatures and forged signatures in past literatures were reported as to show the variation between true and forgessignatures in review-directed forensic research.

4.2 Independent-Samples t-Test

Independent-samples t-test; Independent-samples t-test can be used to compare the means of two independent samples if the relevant conditions are met. $H_0: G = F$; $H_1: G \neq F$; G indicates real signatures; F indicates fake. A normally distributed continuous measurement like height, width or area would have independent samples t-test as a suitable test, provided all independence and variance assumptions hold true, as relevant.

4.3 Mann-Whitney U Test

When conditions to employ a parametric test are not met, non-parametric tests, like the Mann-Whitney U test, may be employed. This may be done when the sample sizes are small, data is skewed, or if there are any outliers and it is not evident if the data meet normally.

4.4 Paired Statistical Tests

Paired analyses may be more applicable if signatures are being compared between writers, or when replicated observations of the same subjects are acquired. When differences are assumed to be roughly normally distributed, the paired t-test can be employed; however, the Wilcoxon signed-rank test offers a non-parametric equivalent. A key factor separating independent and paired observations of a particular sort-and one with substantial relevance to signature analysis-is that observed signature data taken from individual writers may well not be statistically independent.

4.5 Correlation Analysis

With correlation you can see if features are tightly connected. As width and area might naturally correlate in so far as larger signatures have more pixels allocated to them, they may naturally be heavily correlated and, hence a redundancy and as

part of the feature selection process may be rejected. The Pearson calculation of correlation coefficient is. If variables are ordinal or are not normally distributed Spearman's rank correlation is generally preferred.

4.6 Effect Size

Statistical significance does not imply practical significance and it does not communicate group-differences in size. Measures of group-difference, known as effect sizes (for differences), address group differences. The effect size when comparing two groups-called Cohen's d-is $d = (X_1 - X_2)/S_p$, where S_p represents the pooled standard deviation. Effect size, with regard to forensic studies, are quite important as the size of a statistically significant group-difference might be too small to yield practically useful discriminating differences.

4.7 Multivariate Analysis

Many times, morphology doesn't act in isolation. In such situations multivariate analysis may provide better explanations than single character analysis. Typical procedures are Principal Component analysis, Linear discriminant analysis, quadratic discriminant analysis, cluster analysis, logistic regression, and multivariate analysis of variance.

With PCA one is attempting to find linear combinations of original features in order to reduce dimensionality, while still explaining a high percent of variability.

With LDA we try to find linear combinations which differentiate classes among the ones already known.

4.8 Machine-Learning Classification

Within this area, machine-learning algorithms are proving to be indispensable. Of the many classifiers now employed, SVM, Random Forest, k-NN, ANNs, CNNs and deep CNNs seem to be most prevalent. Studies investigating the reduction of featured points out that if representative global and local features are selected for use, verification accuracy is improved. It should be said though that some steps in designed feature extraction can be avoided using some deep learning methods and allowing images to learn their own representations directly from the inputs.

It does appear that this method requires significantly large training datasets and lack of obvious explanation from morphological features that have been measured.

5. Comparative Table of Approaches Reported in Literature

Study/Approach	Feature/Method	Data Type	Statistical/Computational Approach	Major Contribution	Major Limitation
Plamondon & Lorette (1989)	Static and dynamic signature characteristics	Online/Offline	Pattern recognition approaches	Established major concepts in automated signature verification	Early computational limitations
Hafemann et al. (2015)	Geometric, graphometric, directional and other handcrafted features	Offline	Feature-based verification	Comprehensive review of offline signature verification features	Offline systems lack dynamic information
Ebrahim et al. (2018)	Global and local feature selection	Offline	Feature-selection methods	Demonstrated importance of selecting informative	Performance dependent on

				features	dataset/protocol
Hameed et al. (2021)	Handcrafted and learned features	Offline	Machine learning/deep learning	Systematic review of 56 studies and major research challenges	Strong dataset and protocol dependence
Hafemann et al. (2017)	Learned image representations	Offline	CNN	Demonstrated strong performance using learned representations	Requires substantial computational/data resources
Jagtap et al. (2021)	Multiple feature and verification approaches	Offline	Comparative review	Identified continuing challenges in offline verification	Broad review rather than forensic validation
Recent explainable DL approaches	Local image features and learned representations	Offline	CNN/explainable DL	Potential for verification from limited reference samples	Generalizability to forensic casework remains uncertain
Morphological feature approach	Height, width, aspect ratio, area, perimeter, density	Offline	Descriptive and inferential statistics	Simple, interpretable and computationally accessible	Sensitive to scaling, segmentation and natural variation

Hence, literature progresses from hand crafted geometry-based descriptions toward statistical pattern recognition, machine learning, and deep representation learning. No family of methods works well in every circumstance; performance heavily relied on data quality, feature representation, validation methodology, and type of forged image analysis.

6. DISCUSSION

Morphological features provide an excellent quantitative way of describing the shape and composition of handwritten signatures. One of the biggest benefits of morphological analysis is the interpretability of each measurement; measurements like height, width, area, aspect ratio, etc. can each be clearly described, and measurements are repeatable. This interpretability benefit would be highly valuable for forensic document examination since all results and inferences should ideally be grounded in observation.

Unfortunately, the interpretability does not necessarily make any and all individual morphological measurements indicative of authenticity or deception.

For example, while two signatures may show a marked difference in height, this discrepancy does not inherently mean one must have been forged since a single author can vary the dimensions of his signatures, and can produce signatures which differ in height, width, or overall area. Factors like scanner resolution, image cropping, and degree of rotation or scaling will also heavily impact all the measured morphological features. As a result, preprocessing-segmentation, noise reduction, background deletion, and normalization-must be used before acquiring measurements or the artificially created differences between measurements may make the comparison unhelpful or incorrect. The limits with global morphology are also, obvious as they only represent a comparison of signature as whole; two very different signatures might show almost identical aspect ratio and measured height/width.

A particular writer can naturally vary a signature globally while retaining localized differences in how it is made, and in this context, a morphological test of authenticity that uses only global features will likely be unsuccessful.

Both global and local features can and should therefore be taken; research over the years has found this need particularly

acute for offline signature verification where local, direction-based, graphometric, structural, or other geometric features often need to supplement a measurement that is derived from a description of a signature from its boundaries as a whole. It can therefore be said that local features complement morphological ones for this specific application area, providing useful differences to the features themselves. Also, the problem with skilled forgery should also be considered: a good forgery might mimic the outer boundary dimensions of a good document and that alone is likely to make analysis based on morphology an unreliable detector.

Machine learning, in which disparate characteristics are summed up to obtain a classification, is thus seen as promising since multiple only weakly distinctive features might cumulatively show genuine differences between hand signatures. Learning of features in this manner using neural networks has already demonstrated a dramatic increase in performance, even on recognized offline document evaluation tests, but this does not guarantee forensic validity or the presence of discernable human-understandable relationships. Firstly, test documents can differ from scanned forensic materials.

Test documents can indeed benefit significantly from the use of controlled conditions for acquiring data, not encountered by a questioned document examined by a forensics expert.

Another issue for machine learning tests is statistical dependence; features can and have been trained and then immediately tested by presenting same-writers numerous times during both training and testing. Thus, a model can be tested but has not actually been generalized to unseen authors. Finally, the issue of explanationability arises: when an automated test labels a handwritten signature as genuine or a forgery and no discernible features can be extracted and understood by humans to account for this decision.

7. Research Gaps

7.1 Lack of Standardized Morphological Feature Sets

These studies vary enormously in selected feature extraction, preprocessing techniques, image resolution, normalization and statistics procedures making direct comparison impossible.

7.2 Limited Forensic Validation

Quite often, studies have been conducted using readily available public benchmark data sets as opposed to using actual forensic case materials. Although benchmark data sets have their merits they can be limiting due to the restricted environment under which they are constructed which may not necessarily be an accurate reflection of a questioned document scenario.

7.3 Skilled Forgery Detection

It may not be particularly difficult to identify many simple and random forgeries. A sophisticated simulation or tracing is more difficult.

7.4 Natural Intra-Writer Variation

A real writer does not forge signature in identical manner. We cannot use one specific signature as a model in the future systems; Instead, the possible variation space of genuine signature should be considered.

7.5 Image Acquisition Effects

The measurements for morphology would change depending on scanning resolution, document quality, ink/paper used, compression, light, rotation, and segmentation.

7.6 Small and Imbalanced Samples

The number of authentic and fake exemplars that might be collected and examined in a forensic study may be limited. The statistical power associated with a small number of samples, and the increased risk of over-fitting the dataset are both issues.

7.7 Limited Explainability in Deep Learning

The strength of deep-learning systems as classifiers, the difficulty of explaining their decision processes is a pertinent issue for forensic uses as the premises and conclusion must have a scientific basis.

7.8 Lack of Unified Statistical Reporting

Research does not provide consistent details on effect size, confidence interval, statistical assumptions, cross-validation method or estimates of uncertainty. A more standardised report of statistics would advance replication and scientific comparability.

8. Future Directions

Future research should focus on integrated methods of analysis, combining morphological study with statistical modelling and machine learning. The focus of morphological study should first involve development of standard feature protocols (e.g., a basic set of features is height, width, aspect ratio, area, perimeter, compactness, eccentricity, density, connected components, endpoints, loops, skeleton related features etc.). Secondly, global and local descriptor analysis should be attempted; by breaking a signature into regions spatial difference will be found where global metrics might 'dilute' this effect.

Statistical methods could take account of: 'replicate measurements and writer variability'; hierarchy or mixed effects models may be of particular use as it is unlikely that several signatures are written by a single individual.

Results of these statistical models need to take into consideration both statistical and practical significance (as opposed to purely 'p values') effect size and confidence intervals. As previously mentioned, validation should focus on writer independent data sets. Explainable machine learning could be used to identify both relevant classes and highlight to the investigator the reasons for particular diagnoses, it might even identify those factors the writer-independent analysis of the morphological data. Forensic laboratories and academia need to consider larger, more representative data sets encompassing, 'variation due to the natural variations of writers, writing instruments, document conditions and levels of falsification skill levels'.

Overall, however, future analysis must consider a graded system rather than genuine/forgery with each signature receiving an assessed value of evidential weight.

9. CONCLUSION

Morphological analysis plays a vital quantitative role in the detection of signature forgeries. Morphological measurements such as height, width, aspect ratio, area, perimeter, compactness, eccentricity, pixel density, and textural qualities quantify different aspects of the signature shape and can be used as an adjunct to visual examination. It is evident from literature that no single signature attribute possesses discriminating power sufficiently high to allow signature validation alone.

Combinations of the globally based measurements together with some of the local, structural, graphometric, and texture-based metrics show highest discrimination ability.

For the quantitative evaluation of difference between signatures, statistical techniques are important and machine learning techniques provides the ability to integrate various features together. However, it should be recognized that conventional analysis techniques have some limitations as the real signatures contain natural variation, forgery with great proficiency can mimic the global shape accurately, and even minor variation of acquisition devices or conditions can lead to significant variation in some feature measurements. High performance over the control database doesn't necessarily equate to forensic validity. Future will show hybrid and explainable systems that support rather than replace traditional forensic practices with computational ones.

Morphological features have an additional advantage as the relationship between visual observation and computational processing is clearer in the form of morphological parameters. With sound methodologies, appropriate validation statistics, representative datasets and transparent and informative reporting, morphological analysis of handwritten signature can become an extremely valuable component in the forensic examination domain in a repeatable and objectively sound manner.

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