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Dynamic signatures: A review of dynamic feature variation and forensic methodology

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Abstract

This article focuses on dynamic signatures and their features. It provides a detailed and critical review of dynamic feature variations and circumstantial parameters affecting dynamic signatures. The state of the art summarizes available knowledge, meant to assist the forensic practitioner in cases presenting extraordinary writing conditions. The studied parameters include hardware-related issues, aging and the influence of time, as well as physical and mental states of the writer. Some parameters, such as drug and alcohol abuse or medication, have very strong effects on handwriting and signature dynamics. Other conditions such as the writer's posture and fatigue have been found to affect feature variation less severely.

The need for further research about the influence of these parameters, as well as handwriting dynamics in general is highlighted. These factors are relevant to the examiner in the assessment of the probative value of the reported features. Additionally, methodology for forensic examination of dynamic signatures is discussed. Available methodology and procedures are reviewed, while pointing out major technical and methodological advances in the field of forensic handwriting examination. The need for sharing the best practice manuals, standard operating procedures and methodologies to favor further progress is accentuated.

Keywords: Dynamic signature; forensic science; forensic handwriting examination; variation; evidence evaluation

1. Article motivation and structure

The field of forensic document examination has changed significantly over the last decades. The rapid development of computers, mobile devices such as Smartphones and tablet PCs, Smartpens, and other devices has given way to an explosive increase in connectivity and data generation. This has affected forensic document examination in many ways, including the domains of text processing and printing, imaging and image treatment, high fidelity reproduction and counterfeit detection. These developments have also led to novel skills and *modi operandi* for forensic examiners and criminals respectively.

While it seems that the increase in use of computers should have resulted in the progressive abandonment of handwriting and signatures, the reality is quite different. The most common form of signature is still by far the handwritten signature. It is a behavioral biometric identifier linked to a physical entity, a given person signing, that serves as a sign of authenticity and intent. Handwriting and signatures are highly practiced, personal skills, which continually develop through years of practice. The dynamic signature, a digitized version of the analog handwritten signature, is becoming a common solution for businesses, concurring with paper-based signatures. With the rise of high-quality acquisition hardware such as connected pens and high-grade sensors, signatures can be written directly onto digital documents. This eliminates the need for printing and scanning paperwork, making the processes of signing faster and cheaper for businesses. Dynamic signatures are mostly embedded into documents by encryption. In this way, the signatures are strongly linked to both the signed document and to the signer, making them adequate replacements for paper signatures.

The dynamic signature presents a challenge to the forensic document examiners because of the changes in data nature and volume. These changes mean that adaptations in evidence processing and evaluation are necessary as well. The field of handwriting and signature dynamics is of interest not only to forensic practitioners, but also to biometricians, medical practitioners and neuroscientists. Considering the recent developments in the field and the lack of a comprehensive summary for forensic science applications, it seems appropriate to critically review the current state of the art. This review should illustrate the purpose and methodology of examination, introduce common terminology and provide information about signature feature variation and influencing parameters.

The present article defines the dynamic signature and its properties. In Section 2, questions of terminology are considered, in order to clear up difficulties originating from the ambiguity of diverse forms of electronic signatures. Section 3 elaborates on frequently available dynamic features and our knowledge about their variation in standard conditions. Subsection 3.1 deals with measurable dynamic features and their application to forensic purposes. The following subsections, 3.2, 3.3 and 3.4, review physical conditions, temporary states (e.g. intoxication) and hardware-related parameters respectively. In Section 4 a critical review of published methodology in forensic examination of dynamic signatures is given. Finally, a brief critique of current state of the art and some future perspectives are provided in Section 5.

2. Defining the dynamic signature

The word signature, as defined by the Merriam-Webster dictionary, has as many as seven different meanings. Primarily, “signature” denominates the handwritten signature of a person, but it can also be seen as distinctive mark serving to set apart abstract entities, such as a corporation, a group or a project. While dynamic signatures conform to the first definition of a signature, many other types do not, such as cryptographic signatures (“electronic signature”), stamps or fingerprint-based signing. Curiously, the word signature designates both the act of signing, giving it a legal meaning, as well as the result of the signing process. Sometimes, the term signature is also used to refer to the writing process producing the trace. Many other meanings are associated with the concept [1].

"Definition of signature:

1	*a:*	*the act of signing one's name to something*
	b:	*the name of a person written with his or her own hand*
[…]		
6:		*something (such as a tune, style, or logo) that serves to set apart or identify; also: a characteristic mark*
[…]"		

In the remainder of the present article, the word "signature" is used to describe the data resulting from the "recording" of the execution of the signing behavior. This data may take either the form of a graph (physical or digital ink), or numerical data, such as video recording, text data or images. Descriptors of the data will be referred to as either characteristics or features. Features related to the movements producing the signature will be referred to as dynamic features. Features related to the product of the executed movement, the graphical representation of the signature, will be referred to as static or graphical features.

The signature is a "snapshot" of the individual's movement, given his state of health and mind, at a specific moment. Signatures are the result of a complex behavioral pattern, resulting from the activation of various regions in the human brain concerning functions such as linguistics, motor function and motor and visual feedback [2]. Not only is the human brain facing a demanding task when planning the movement, but it is also actively working during the execution of the signature. The signature movements need to be executed by the coordinated effort of different effector muscles situated in hand, wrist, fingers and shoulder [3, 4]. The multiple possible situations, physical states and deviations in movement control and execution create what is commonly referred to as "variation".

The human body and brain are not as reproducible as machinery, which creates 'natural' variation within signatures from the same writer. Modified circumstances and state of the writer can create even stronger variation in the final product. Movement can be roughly separated into the planning and the execution stage. In both stages, there are many variables to be controlled and influence parameters to be accounted for. According to Huber and Headrick [5], this variation is due to parameters, called factors by the authors, which can be classified as being either *intrinsic* or *extrinsic*.

Intrinsic factors are parameters over which the writer has some degree of conscious control. They are generally circumstantial in nature. Huber and Headrick further catalog several types of intrinsic factors, notably "imitation" (emulation of perceived writing characteristics), circumstantial factors (e.g. posture, writing substrate, writing instruments, situational constraints), temporal states (e.g. induced states from alcohol and substance abuse) and educational factors. Several categories, such as substance abuse might require further subcategories relating to the effects of the substance. Common substance classes influencing handwriting and signature include depressants, such as alcohol, and stimulants, such as caffeine and nicotine, or various other effects from medication. The effect (e.g. slower/higher writing speed, lower/higher pen pressure variation) and effect size depend on the dosage and the "efficiency" of the consumed substance and the metabolism absorbing it. Extrinsic factors are conditions out of the writer's conscious control, for example age, infirmity and injury, and handedness.

Dynamic signatures are a type of handwritten signature, characterized by a chronological sampling of the signature movement. They differ from physical signatures in their acquisition method and the recorded features. "Physical" signatures are acquired on a substrate, mostly paper, which carries the ink trajectory, called the signature. Handwritten electronic signatures are recorded by digitizers, which may or may not need a "substrate." Many different kinds of digitizers exist, but signature pads are the most common digitizers. These pads sample the analog signal of the movement of the pen on (and sometimes even above) the pad spatio-temporally and create a dynamic signature. Due to the sampling, loss of both spatial and temporal resolution is inevitable. On the one hand, the resulting signature is less detailed and less continuous than a paper-based signature. On the other hand, the dynamic signature records previously "inaccessible" data, such as precise measurements of speed, acceleration, pen pressure, stroke direction and timing information.

Dynamic signatures are known under various names in research fields. Researchers have used many designations, such as "Biometric Signature", "Electronically captured signatures," "Digital Dynamic Signatures," "Handwritten Electronic Signatures," "Online Signature" or "Dynamic Signature" [6-11]. While the previous expressions all designate the same object, some names like "Electronic signatures" or "Digital signatures" are very similar, but refer to larger concepts or different kinds of signatures. Specifically, the term "digital signatures" refers almost exclusively to cryptographic signatures based mostly on Public Key Infrastructure (PKI), while the term "electronic signatures" is a legal term, often encompassing both cryptographic, handwritten and any other kind of "computer-based" signature. A visual representation of the taxonomy is proposed in Figure 1. Forensics has not found a consensus on terminology yet, but the biometrics field often refers to either "online signatures" or "dynamic signatures" [12-18]. A summary of common terminology with a brief description can be found in

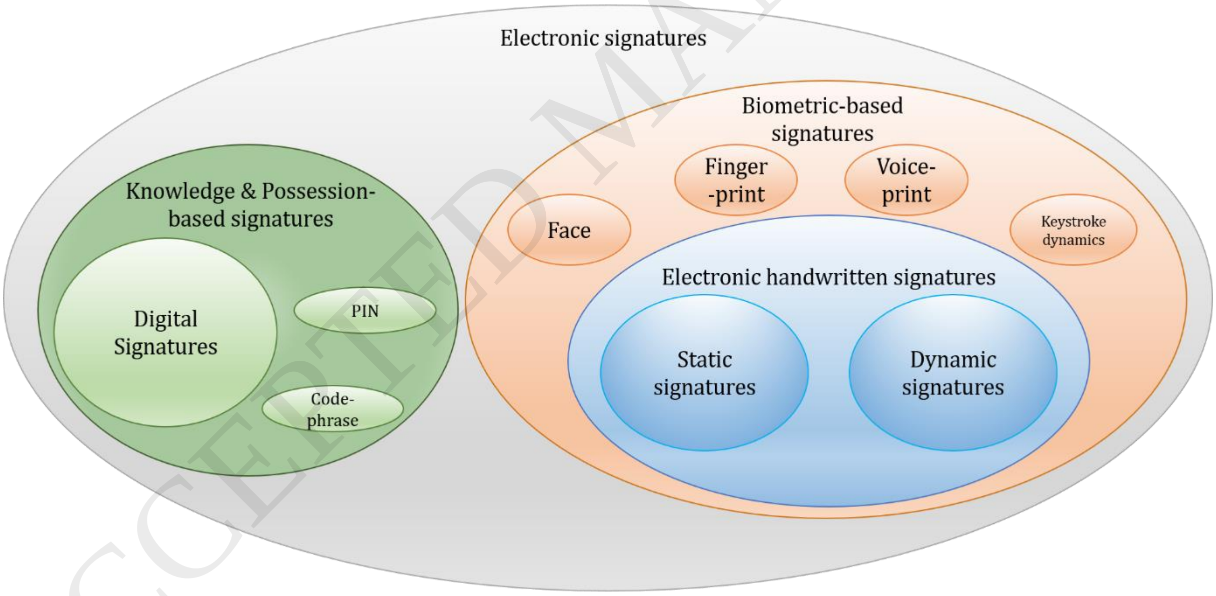

Figure 1 - Taxonomy of electronic signatures

Table 1.

The term “dynamic signature” differentiates the signature from a scanned handwritten signature (or *static* signature) that does not contain any of the information related to the execution of the signature (e.g. timing, pressure, speed), while at the same time omitting reference to its digital nature. Any reference to “online,” “electronic” or “digital” may cause confusion, as they may relate to cryptographic signatures. Further confusion arises because most digitizers use cryptography to guarantee safety of the biometric data and digitizer authenticity. Dynamic signatures also often use digital signatures in order to create a secure link between the signature and the digital document, as well as prevent tampering.

The authors highly recommend using the “dynamic signature” designation, as it is logical, coherent and short. This proposed terminology corresponds to the one included in Harralson’s work [6]. It minimizes the potential for misunderstandings as no computer-related words are included and it stresses the essential properties, the dynamics of the signature movement. Whatever choice of terminology will be adopted in the future, it is essential to define the expression and scope coherently in order to avoid misunderstandings and sharing misleading information.

3. Digitizers, Dynamic Data and Variation

Dynamic signatures and the related dynamic data depend on multiple parameters, all influencing the signature and causing variation through different ways. Some of these parameters are linked to the hardware and measurement instruments, while others are more closely linked to the interaction between the writer and the writing implements; lastly, some are intimately linked to the writer. A review of a selected few parameters and their impact on the signature dynamics are presented in the next subsections.

3.1. Dynamic feature variation and discriminative power

Dynamic signatures record dynamic data such as timing and pressure information during the signing process. This information is not recorded quantitatively in physical or even static signatures and can only be inferred from the signature's graphical features, such as the line width or the groove depth created by the pen. Authors have considered several methods to provide better approximations for inference of dynamic features [24-28] on physical signatures, but there is much uncertainty involved in the determination. Having accurate measurements makes statistical treatment and data evaluation worthwhile and may lead to a more rigorous signature examination process. The field is very new to forensic science and has not yet received much interest from the forensic research community. Thus most of the available data is provided by research into biometric verification systems. Literature on dynamic signature variation is scarce, as most biometric literature focuses on classifier performance. Data on individual feature performance, as well as reasons for erroneous classification are often left for further research.

Currently, the most commonly used dynamic features are pressure, velocity, acceleration, jerk, and pen angles (e.g. tilt, altitude, and azimuth), timing information and in-air (or pen-up) measures. Up until now these features have mostly been used through qualitative features, having been inferred from an ink trace. Forensic handwriting examiners (FHEs) have used concepts such as shading, tremor, fluidity, line quality, and tapering to describe these various dynamic qualities of signatures and handwriting. Table 2 describes the correspondence between measurable dynamic signature data with the qualitative features used by FHEs. Quantitative descriptors of dynamic features have been used in biometric verification systems, with little research from a forensic science point of view. Eoff and Hammond [29], for example, achieved an 83% rate of correct-writer classification in a population with 10 writers providing genuine samples using only speed, pressure and pen tilt. The discriminative powers of the diverse dynamic features have often been inferred through study of correct verification rates. Very few authors have studied separation of the variables, clusters or distributions in detail.

The temporal derivatives of position, meaning velocity, acceleration and jerk, are mostly recognized as discriminative and useful features. They are often included in biometric verification systems [30], as well as used as a criterion in forensic examinations through fluidity, shading and line quality evaluations. Inversions in velocity (NIV) [31] are often used in movement and neuroscience to determine motor control, movement efficiency and automation. Teulings et al. [32] use the time-integrated squared jerk to characterize smoothness of movement. This feature has been used in many "therapeutic" or "developmental" handwriting studies to characterize movement quality. It is also included in commercial software such as the MovAlyzeR suite [33] and may prove useful for the forensic examiners for detection of tremor, a common sign of disfluidity [5].

Several studies indicate that velocity and acceleration, as well as their variations are interesting features in simulation detection [34-38]. Velocity and acceleration in simulations are often lower than in the genuine signatures. Jerk appears to be lower in text-based genuine signatures [35, 36] in comparison with the simulations, although the other signature styles do not show significant differences. Many studies have used velocity, acceleration and jerk as useful features for signature verification, as biometric literature reviews show [30, 39].

The writing pressure is a more controversial feature, as results differ between studies. This may in part be due to the different measurement schemes, as well as hard- or software-related problems [38]. Hook et al., Tytell, as well as Ostrum and Tanaka [24, 25, 40] all found in their respective studies that pen pressure is a stable feature in a genuine signature. Forensic practitioners have been citing pressure as a discriminating feature for simulations for nearly a century [41-43]. Unfortunately, very little empirical evidence for this claim has been produced.

Kholmatov and Yanikoglu [44], however, appear to provide support against the usefulness of pen pressure. Other more recent studies do imply that the mean pressure is a discriminating feature [35, 36, 45-47] for forensic purposes. Some of their results [35, 36, 46] challenge a long-established theory, which predicts an increase in the pressure average in simulations. This theory involved the idea that there is increased stress on the person while creating a simulated signature [48-52], which affects movement execution. Pressure may also be of use as a local feature, using the continuous data provided by digitizers, rather than a summary in the form of the mean. Caligiuri and Mohammed [53] cite the absence of variation in the pressure signal as a feature of simulated signatures. Pressure variation and dynamics may carry just as much information as the mean value.

Pressure is promising for use in forensic purposes, but has suffered from measurement reproducibility problems in the past [38]. It must also be noted that pen pressure may be measured axially or orthogonally to the surface, which complicates data comparison when two distinct digitizers were used. Many studies support pressure as a good feature for signature comparison. Even though recent results have been encouraging, the examiner should check carefully the measurement method and reproducibility for the digitizers involved.

In-air pen movements constitute a category of features that is exclusively available in dynamic signatures. Terminology varies from “Pen-Up Movements,” “Pen lifts” and “non-inking strokes” to “In-air Movements”. These terms designate the strokes when the pen (or writing instrument, generally speaking) is not in contact with the digitizer tablet (or writing medium). Dewhurst et al. [54] studied these movements for forensic purposes and found that signature movements stay fluid and continuous even when the pen leaves the writing surface.

In-air movements are often not straight linear movements from endpoint to starting point, but are curvilinear, continuous movements defined by said end and starting points of the successive on-surface strokes. Dewhurst et al. also found that in-air data (such as the trajectories) are as discriminating as on-surface data and might even be better suited for forensic purposes, as they cannot be seen on a signature image. Sesa-Nogueras et al. [47] found that both in-air and on-surface movements contain information relevant to handwriting and writer discrimination. The study also showed that information between in-air and on-surface strokes is not completely redundant. By combining information from both stroke types, better results could be obtained.

Dròtar et al. [55] also showed that handwriting in-air movements contain different information than the on-surface strokes. In his study, he found that in-air movements can be used to effectively distinguish healthy control groups and Parkinson’s Disease patients. In-air movements produced better accuracy than on-surface movements and the combination of both types of movements only marginally improved the in-air movement results. Other related data, such as the number of pen lifts, have often been used in “global” feature-based biometric systems and do not necessitate the recording of dynamic data while the pen hovers above the surface. The available studies suggest there being high information content and potential for in-air features for forensic and medical purposes.

Pen tilts and angles are relatively rare features, as they are only recorded on a few digitizers or when using special accessories. The Apple iPad when used with an Apple Pencil or the Wacom Intuos Pro tablet, are examples of digitizers capable of recording these features. Franke [38] studied pen tilt (on a Wacom Intuos Pro) in a population of 30 writers and found out that a majority of people present a pen tilt between 50° and 60°. Many people differ in their pen-angle behavior, but a majority of people exhibit a range similar to these standard values.

As for Pen-azimuth, Franke [38] noted that left and right-handed people have different azimuths. According to her study, pen azimuth values are more heterogeneous. Still, some values are more frequent, with a population mean value of 140° and a standard deviation of around 20° for most writers. Research done by Lei and Govindaraju and Fierrez-Aguilar et al. [56, 57] suggests that these features destabilize the verification system and lead to poorer discrimination.

Some other authors observed that pen tilts and angles have improved the verification rate in their systems [45, 58]. Zareen and Jabin [58] have observed that a false acceptance rate on a mobile device decreases steeply when integrating pen-tilt features. Franke describes pen tilt and pen azimuth as discriminatory features for writers signing their names [38]. Sesa-Nogueras et al. [47] found that pen tilt and azimuth have lower entropy (thus lower information content) in on-surface strokes, but contain more information for in-air movements. Pen angles have not often been used in a forensic context, so their efficiency remains to be determined.

Most of the dynamic features need to be further explored in the forensic context. For instance, many questions regarding the features' long-term stability and short-term variations in time need to be researched. Additionally, some studies and models of the signature movements, such as the work done by Plamondon et al. [59-64], imply that there are strong correlations between the signature trajectory and the associated dynamic features. These correlations between features mean that evaluation of univariate features may be inadequate for evidence evaluation in forensic science. In order to better approximate the strength of evidence, multivariate data evaluation may be necessary.

3.2. Physical conditions - Age, health and posture

Movement does not depend solely on the planning and effectors of the movement, but it is also influenced by the physical state of the writer. Casework has led FHEs to research the effects of body posture, age and infirmity, as well as medication, etc. Most of these parameters are intrinsic (as described by Huber&Headrick [5]) and often circumstantial in nature. While the effects of such conditions on the static signature trace have been studied and documented, they may have far-reaching consequences for signature dynamics as well.

Sciacca et al. [65] investigated the effects of posture on signature characteristics in order to gain insight into the comparability of handwritten documents and graffiti. Their results strongly suggest that within the signatures of one writer, variability is not different whether the person is in a sitting or a kneeling position [66, 67], as long as the writing surface is horizontal. More variation and changes have been observed when the writing surface is vertical [67].

Equey et al. [68] investigated the changes in width, height and aspect ratio when signing in multiple positions. They tested four different conditions: first sitting on a chair with the writing substrate on a horizontal table, second standing up with the writing substrate against a vertical wall, third standing up while holding the writing substrate on a hard board and fourth standing up with the writing substrate on a horizontal table. Their results showed that signature size strongly varies between the positions, leading to increased variation of aspect ratios. The greatest changes were observed when the person had to hold the writing substrate on a board while standing. The authors suggested that the instability of the writing substrate may actually cause more variation than the position itself.

An older study performed by Evett and Totty [69] states that for handwriting, variation between sessions may have more effect than the studied effect. This complicates the interpretation of the position studies, which had not considered this. Thiéry et al. [70, 71] suggest that some of Equey's and Sciacca's results may have been misinterpreted, as their follow-up study showed no clear impact of position in a classification task. They further suggest that pressure strongly depends on posture and thus may be a good indicator for inferring the writer's posture. Overall, the authors conclude that a "sampling session effect," rather than an effect of position, is the cause of most of the variation observed in the previous studies. They are unable to give a generalized answer on the importance of the writer's position in writing variation, when signatures are not acquired during the same session, as the inter-day variation seems to have bigger effects than variation due to position. Finally, the influence of body position appears to be limited, but inclination and stability of the writing surface are high impact parameters.

Forensic handwriting examiners are frequently working on wills or on dated signatures. In such cases, circumstances are often such that no new reference materials can be produced. The signer may have passed away, his handwriting may have degraded or changed in the mean time, obliging the forensic scientist to work with the available contemporaneous reference materials. Along with aging, comes an increased risk for illness or infirmity. Case-specific context information about the long-term evolution of the signature due to an illness or injury is necessary. If no such material is available, acceptance tolerances in the comparison process must be adapted to compensate for the lack of more adequate reference materials.

In order to work in the presence of these difficult conditions, studies on illness, aging and degradation of motor function have been a priority for forensic examiners. It is known that aging is accompanied by a significant decline in cognitive functions in mammals [72]. "*Executive function, which includes processes such as cognitive flexibility, cognitive tracking, set maintenance, divided attention, and working memory, is a cognitive domain impaired in aged humans and monkeys and is thought to be one of the first functions to decline with aging (Moore et al., 2006; Rapp and Amaral, 1989).*" Naturally, this decline also affects handwriting and signature behavior, as was very well summarized by Caligiuri et al. [53, 73].

Normal aging effects include increased reaction time, decreased speed, increased movement time, increased variability and reduced grip strength. These signs are not exclusive to aging and may also be a result of diseases or medical conditions [53]. For many conditions in handwriting, such as aging, the effects are often strongly dependent on the individual, as shown by Galbally et al. [74] for aging dynamic signatures and other authors in biometrics [8, 56]. In forensic casework, access to adequate and contemporaneous reference material is highly recommended [5, 75, 76].

Galbally et al. [74] conducted a long-term variation study for 15 months, with six signing sessions and 46 signatures per user. His results showed that dynamic features vary more strongly than static features. In summary, the writer shows less variation in the spatial representation than with the execution dynamics, which may be subject to change [74, 77-79]. The authors of the study also noted that dynamic features are more strongly affected by "aging" and that these effects influence system performance in verification tasks. The downside of the work by Galbally et al. is the low number of samples per session as well as the absence of any training before signing, allowing the user to get accustomed to the signature pad. It is doubtful that four signatures are sufficient to represent a signature's variation. Sciacca [65] for example recommends at least eight repetitions for words and letters when evaluating handwriting evidence.

Mergl et al. [80] found that younger individuals write faster and more fluidly than older individuals. Guest [14] corroborates these results. He found that with age, signatures tend to be written more slowly, but noted no decrease in reproducibility with age. He did report that features related to execution time and pen dynamics were significantly different in his three different age groups. Age and contemporaneous material are important parameters in forensic handwriting examination, even more so when dealing with dynamic signatures.

Many medical conditions (e.g. Parkinson's Disease, Obsessive-Compulsive Disorder, Attention-Deficit/Hyperactivity Disorder, Alzheimer's Disease, Huntington's Disease and depression, [53, 81-85]) affect the handwritten signature. However, a detailed discussion of the various effects and causes surpasses the scope of this review. The forensic examiner should be aware of the effects of these conditions on dynamic information. Particular attention has been paid to neurodegenerative disorders [53, 55, 77, 85-90] and their symptoms, in particular Parkinson's Disease, due to their frequent appearance in elderly people. Those conditions are often relevant for the forensic examiners when a will is being contested. Medical conditions such as Parkinson's Disease are apt to change motor planning, inter-limb coordination and writing size, having large impact on dynamic features. Teulings et al. [32] for example cite movement control problems, slowness, reduced movement amplitudes and prolonged deceleration phases as classic signs for Parkinsonism.

3.3. Temporary states - Sleep deprivation, alcohol and intoxication

Handwriting and signatures being a "snapshot" of the writer's current state, many other parameters influence the "natural" execution of the signature movements. These may be linked to his physical state (e.g. injury, fatigue, sobriety, effect of medication/drugs/substances, recovery from illness) or to his emotional state (e.g. stress, anxiety, emotion and depression). Emotional states of people are notoriously difficult to study, making physical state research more popular. Research on such states is relevant to forensic casework if the parties claim special circumstances, such as intoxication, extreme fatigue or stress (e.g. due to coercion).

Several studies have been conducted on the impact of sleep deprivation and fatigue on handwriting. Durmer and Dinges [91] describe the adverse effects of sleep deprivation on psychomotor performance and motor control. While these effects apply for long tasks, participants are generally able to gather their attention for short tasks (below 10 minutes) according to Bonnet and Rosa [92]. Huber and Headrick [5] summarize several studies and sources on sleep deprivation, notably Roulston's and Remillard's unpublished studies. Both conclude that lateral expansion was found to increase with fatigue. Remillard also noted bigger writing size and slower writing speed.

Conduit [93] provides a summary of more recent existing literature on the subject. In his article, he critically analyzes several other studies, including that of Tucha et al. [94] on the same subject, mainly for methodological weaknesses due to the small sample size and the biasing effect the experiment order might have had. Tucha et al. [94] found that writers increased spacing slightly in handwriting when deprived of sleep. Bigger differences were observed in the handwriting kinematics. The study found that handwriting under sleep deprivation showed lower writing times, higher maximum velocity of ascending strokes and a decrease in numbers of velocity and acceleration inversions. Increases in maximum accelerations (positive and negative), as well as maximum velocity in descending strokes were weaker.

Conduit [93] only investigated the spatial features of handwriting in his study, but found that these remained consistent, except for word and letter spacing. The author also found that the increase in spacing when subjects were sleep-deprived also extended to handwritten signatures. A study by Jasper et al. [95] investigated the effect of fatigue on handwriting and tested the effect when sampling within fixed time periods. The results of this research showed differences in handwriting features according to a cycle, the circadian rhythm. This rhythm is a kind of biological clock, working in a 24-hour cycle, with recurrent periods of fatigue or alertness, depending on the time of day. The authors show that handwriting fluency, quality and signature speed are not affected by sleep deprivation, while handwriting kinematics do vary according to the "fatigue" level of the participants.

In another article by the same authors [96], invariance in signature execution is attributed to the lower complexity of the signature task, as compared with handwriting. Handwriting is a compound function involving not only motor control of the arm, wrist and fingers, but also the use of syntactic, semantic and lexical processing. Unfortunately, the study by Jasper et al. suffers from the small sample size, and the reliability of their results remains questionable. Most studies agree that short duration and highly automated tasks such as signature may be performed normally even when subjects are sleep-deprived [92, 94, 96].

Another subject of interest in forensic handwriting examination is substance consumption. Different kinds of substances may produce varying effects on the motor planning and/or execution. Some substances are psychoactive, while others affect the effectors (e.g. muscles). For the sake of illustration, psychoactive substances can be classified according to their effect on the nervous system, being either depressants (slowing the function of the nervous system), stimulants (accelerating the function of the nervous system) or hallucinogens (altering perception of reality, space and time). Many other substances may be contained in medication, narcotics, beverages and food. As substances have different effects on the system, effects on the handwriting and signature are expected to be different as well. Few authors have studied these effects on dynamic signatures, but several articles on the subject mention changes in signature dynamics subsequent to consumption. Caligiuri and Mohammed [53] provide a summary of medication and substance abuse effects on the handwriting and signature movements.

Alcohol is a substance than can have temporary or permanent effects. Alcohol works as a depressant on the central nervous system and may cause euphoria and intoxication in individuals. Huber and Headrick [5] summarize some studies treating the influences of alcohol on handwriting, finding a total of seventeen effects on handwriting, all the while being critical about the applied methodologies and reliability of the studies. Alcohol influences longer writing tasks more strongly than shorter writing tasks such as signatures, much in the same way that fatigue does. Huber and Headrick cite the irregularity or increase of pen pressure due to high Blood Alcohol Concentration (BAC), as well as a decrease in writing speed and an increase in grammatical and orthographic errors, erratic movements and tremor.

Phillips et al. [97] looked into the mechanisms producing the impairments caused by alcohol consumption by using handwriting recorded on a Wacom digitizing tablet. Their results indicate longer stroke lengths with stable stroke duration, a shift toward acceleration to deceleration imbalance, with alcohol intoxication being related to longer acceleration phases and pressure inconsistency for the non-alcohol-dependent group after consumption of an alcoholic beverage. The most notable changes are the prolonged acceleration phases and longer strokes, while stroke duration stays comparable. This indicates a change in writing behavior, specifically velocity and acceleration, while being under the influence of alcohol. The authors also state that mean pressure is not affected by alcohol consumption, although the pressure variations are affected. This was observed through the decrease of standard variation in the sample, implying a “flatter” pressure profile. Huber and Headrick [5] also state that effects on alcohol-dependent subjects may differ from regular people, as their features may become less variable when alcohol is consumed.

Results by Phillips et al. [97] corroborate Huber’s statement, although they are based on a very small writing sample, containing only four occurrences of the cursive letter “l”. Asicioglu and Turan [98] investigated the handwriting of 73 people after consuming alcoholic beverages. Breath alcohol content was measured for every participant and effects of dosage and consumption were described. The study uses qualitative assessment of discrete features to compare handwriting in sober and non-sober conditions. The results corroborate the previously cited studies. The authors observed increases in “casualness” and “sloppiness,” letter height, word length, grammatical and orthographic errors, spacing and number of tapered ends. The tapered ends are argued to be indicative of high-speed execution. The authors also argue that while execution of strokes is often faster while inebriated, pauses may be longer and thus may compensate the overall execution time in some cases.

Interestingly, the authors have also observed the inverse effects, but less frequently. Overall, increases in writing times are more common (~70-80% of the sample), decreases being more uncommon (~20-30%) and no changes being the rarest phenomenon (~1%). The authors also state that the level of breath alcohol may not be a good indicator for effect size, as some participants with low breath alcohol levels showed large impacts, while others with high breath alcohol levels showed little impact. Still, the authors found a correlation between breath alcohol level and height, angularity and tapered ends (and thus speed).

Shin and Okuyama [99] used a dynamic signature verification system with several writing conditions to determine effects of alcohol on verification performance and to find features useful for detection of alcohol intoxication. They noted that the effects of alcohol fluctuate in time and were most pronounced 35 minutes after consumption. The effect progressively increases and decreases, as would be expected due to the progressive metabolizing of the alcoholic beverage. The authors propose four features to detect alcohol intoxication, namely average time needed to complete a signature, average pen pressure, pen velocity and stroke angles. Pen pressure and average time drop with alcohol consumption (by 30% and 8.8% of the original values), while velocity and internal angles increase (by 22% and by 10%). Velocity is the only feature to show a sharp drop from 110% to 80% of the original value between the signature session at 45 and 55 minutes after consumption.

The study by Shin and Okuyama corroborates information pointed out by the other studies in respect to the increased variation of dynamic data after consumption of alcohol. Signature dynamics and verification rates are both affected by alcohol consumption, but effects depend highly on the metabolizing of the ingested alcohol.

Other frequently consumed substances are caffeine and nicotine. Tucha et al. [100] investigated the effects of caffeine, a widely used stimulant, on motor performance. He administered controlled doses of caffeine (from placebo to 4.5 mg) with a caffeine-free coffee substitute to 20 right-handed adults. The experience investigated performances on a Wacom digitizing tablet using a short German sentence. The author looked at individual characters and sentences, while considering the metabolizing of caffeine. The study showed that only high doses of caffeine significantly affect writing behavior, with levels that could cause nausea in some of the participants. The parameters that were most affected were writing speed and acceleration on the individual elements, while the speed on the entire sentence remained relatively unchanged.

Tucha et al. [101] conducted a similar study on the consumption of nicotine as per nicotine chewing gum, with doses of 2 and 4 mg respectively. His study, performed on 38 smokers and 38 non-smokers showed that nicotine consumption produces higher movement velocities and shorter writing times in both groups. According to the authors, the effects are in proportion with the dosage of nicotine, although they underline a lack of significance observed in their results. In both studies, no mention of pen pressure was made.

Caligiuri and Mohammed [53] also review the very limited literature available on the effects of cannabis on handwriting. In their own study, conducted on a sample of five individuals, they highlight trends indicating movement fluency disruption and movement prolongation. Psycho-motor slowing appears consistent with other cannabis consumption studies. Average pen pressure was found to increase notably for four out of five individuals. The authors also note that sensitivity to the substance might be an issue, due to the fact that one of their subjects was very strongly affected, while the others were less so. We must point out that the study was of very limited scope and that results should be considered with great care.

3.4. Hardware-related conditions

Many types of digitizing devices exist, including gloves, mobile devices, camera-based devices and dedicated signature tablets [102-109]. Every digitizing mode has its own particularities and a different set of recorded measurements. By far the most widespread digitizing devices are dedicated signature tablets and tablet PCs [110], which have been the focus of most forensic studies. These devices can (or must) usually be used with a pen, creating familiar conditions and permitting “natural” signature behavior up to a point.

Writing conditions on paper and digitizer are quite different [111-113], as the surface of the digitizers is smoother and there is less friction between pen and surface [31]. As a result, pen movement on this surface may be perceived as ‘slippery’ or ‘too fast’ and may require adaptation of the signature movements to the new substrate. Alamargot and Morin [111] tested this on young children in order to see differences in writing behavior to check the influence of visual feedback for writing and proprioceptive information in different learning stages. He generally found that the older children tried compensating for the more slippery surface by applying more pen pressure but still end up writing faster and less legibly.

Gerth et al. [31] pursued this experiment with an adult population, comparing paper and ballpoint with plastic pen and tablet surface conditions. Results indicate that adult writers are also influenced by the tablet surface and tend to increase the pen pressure, letter size and writing speed to compensate for the different surface type. The authors also observed that experienced writers adapt to the new substrate in as few as 10 repetitions and were able to decrease writing pressure and other conditions to “normal” levels. The authors also noted that people adapt more quickly if the task they perform is an “automatized” movement process. These results affect recommendations for reference signature collection in dynamic signature cases. People who are not used to signing on tablet screens may need a longer time to adapt their writing and for their variation to stabilize. Thus, multiple or split sessions might be required to get used to the signature pad conditions and produce “natural” signatures.

Another hardware-related issue is the writing space available for signatures and writing. There has been an ongoing discussion on how and to what degree signatures are affected by external constraints, such as predefined signature boxes, lines, display size, etc. These circumstances may force a writer to adapt his signature and thus affect its dynamics. Phillips et al. [114] found that the size of the handwriting can produce extensive changes in the dynamics. Downsizing handwriting requires the writer to adapt stroke number and size, as well as change acceleration and deceleration patterns. Upsized handwriting showed greater accelerations than medium-sized handwriting.

The conclusions of Phillips et al. are in agreement with the hypothesis of Teulings et al. regarding spatial invariance [115, 116], rather than timing invariance. Signatories may also decrease overall speed and add strokes in order to fit their signature into the constraints, which also results in higher signature times. These constraints are traditionally boxes or lines, but may also be windows or prompts to sign, a specific interface or the digitizer screen itself.

Fazio [117] investigated size constriction effects on a Wacom digitizing tablet with a compatible Wacom inking pen, while writing on a sheet of paper fixed to the tablet. Her study corroborates the previously cited results. Additionally, her study shows that the effect of constraint appears to be highly variable. Some individuals' signatures are not influenced at all, while other signers adapt strongly to fit into the constraints. This can sometimes go as far as changing features and parts of their signatures. Notable changes were found in velocity, jerk, overall length, ascender length and descender length. Velocity and jerk showed a decreasing trend with increased constraints.

The only dynamic feature mentioned that did not vary with the size constraint is pen pressure. Impedovo et al. [118] also found the velocity is dependent on size constraints. It is worth noting that context may create circumstances that force people to adapt their signature and produce an obligatory change in signature. Fazio [117] explains the case of the Canadian passport, which contains a box-shaped size constraint. Any signatures touching the box's border are invalid, forcing individuals to respect the size constraint and create a stronger effect than in ordinary circumstances.

Diversity of writing instruments and signature pad surface characteristics are also of interest in the examination of dynamic signatures. As the instruments are not actually transferring ink to the tablet, interactions with the surface differ from regular writing instruments. Most dynamic signatures currently use either pen/stylus or the person's fingers as writing instruments. Signing with the finger conserves the motor programs used for signing with a pen, in accordance to the motor equivalence principle [2, 5, 119]. This means that the execution of the signature is still highly similar, no matter what instrument is being used. Nevertheless, signature reproducibility decreases strongly when a finger is used as writing instrument.

Prattichizzo et al. [120] carried out a comparison of handwriting and drawn shapes using either fingers or pens and found that higher precision was achieved when using a pen. Tolosana et al. [121] recently tested finger, stylus and mixed signature verification. In his study, he found that error rates were lowest for stylus-made signatures, followed by finger-made signatures and mixed comparison. Stylus-based signatures performed significantly better concerning the equal error rates presented, which might indicate better reproducibility. Pens may show different behavior because of the material used, contact surface (pen-tip size), rigidity (deformation of the material), type of nib (or absence thereof) and their cross-sectional shape and diameter.

Goonetilleke et al. [122] state that writing speed is not affected by pen shape, but accuracy is highest when using slim, circular pens. With the rise of Smartphones and mobile devices, signing with fingers is expected to become more common. The variety in writing instruments poses a challenge, as output from instruments such as the finger and pen do not provide the same precision and accuracy.

Many different parameters have been shown to influence the dynamic features of signatures. Table 3 summarizes the major effects on handwriting and signature dynamics reviewed in the preceding paragraphs.

4. Methodology in Dynamic Signature Examination

Forensic science serves the justice system by providing assistance to the decision maker when specialized or scientific knowledge is required to evaluate evidence. The evaluation of scientific evidence often concerns the freedom and fortune of individuals. Forensic science needs to withstand cross-examinations and criticism from scientists, judges, juries and lawyers. For this reason, quality standards (and in some cases gatekeeping measures, such as admissibility hearings) are required to guarantee the necessary scientific rigor in forensic handwriting examination. Furthermore, forensic scientists cannot provide unprocessed analytical results. They need to identify the client's needs, respond to the relevant questions and report these answers in a comprehensible way. This means the standards of quality are not exclusively concerned with the results of an examination, but they do require that examiners provide detailed information about the applied methodology, standard operating procedures, validity of techniques used and the means of communicating the results.

In order to be able to meet the standards of quality, accurate and well-tested methodologies are required. Many authors have published methodologies for physical signatures examination [5, 75, 76, 123-125] or have tried to describe and define the examination of handwriting [126-130]. All of these publications have several things in common: A clear definition of the scope and goals at the beginning of the examination, rigorous analysis and comparison procedures, and a coherent evidence evaluation phase. A solid knowledge of the studied evidence, its features and their variation are necessary to frame and guide the process.

Research on handwriting has greatly advanced since the early stages of handwriting examination [41-43, 131], in response to the severe criticisms laid upon the forensic handwriting examiner's activities [131-135] and forensic science in general [136-140]. Thus, the processes causing variation in signatures, as well as the extent of variation have been studied. FHEs have strengthened their knowledge of the origin of signature movements and the copying processes. Handwriting examination has delved into neuroscience, movement generation on a processing and planning level [2, 52, 53, 64, 119, 141-144], exploring the dynamics of the movement process. It has also incorporated elements of biology and movement science to comprehend movement execution on a muscular (effector) level [38, 120, 143, 145, 146].

Additionally, forensic science has gained insight from the findings in biometrics, with several authors developing movement-modeling techniques [60-64] to represent handwriting movement. There has been a research effort towards descriptor development and feature selection in dynamic signatures [9, 10, 147-150] or adapting automated comparison systems to forensic purposes [151-154]. Furthermore, the criticism has led forensic scientists to provide evidence for expert opinion reliability [155-160], to reconsider the identification and unicity paradigms [161, 162] and to publish their methods [76] and best practices [163, 164].

Franke and Srihari have advocated for "computational forensics" [165, 166] as future development in forensic science, emphasizing the benefits of adding computational techniques to traditional forensic expertise. Their computer-assisted framework might help forensic science progress in a variety of ways, notably speeding up examination of large volumes of data, performing large scale testing and calculating performance and reliability, synthesizing new data sets, as well as standardizing work procedures. This framework is especially useful when dealing with quantitative data such as dynamic signatures.

Many parallels can be drawn between the examination methodologies for physical signatures and dynamic ones, as both types of signatures are recordings of the same process. For example, examination order and structure, as well as qualitative examination procedures can be applied to physical and dynamic signature examination. These similarities might be one of the reasons why few researchers have been concerned with dealing with the more specific aspects of dynamic signatures. Nevertheless, several authors have noticed these methodological gaps and tried to fill them.

Harralson [6] proposes a "methodology", which is actually a decision tree based on signature types (cryptographic, dynamic or static), capture reliability and "sufficient" captured features. The decision tree is certainly useful for the examiner, but it is too limited in scope to serve as an examination methodology and withstand an admissibility hearing. No other publications mentioning complete examination methodology for dynamic signatures can be found. Harralson does, however, mention important concepts, such as digitizer metadata [6, 165, 167, 168], sensor and capture reliability [38, 169] and "sufficient" features, which have been further addressed by other researchers.

Other problems such as device interoperability [121, 148, 149, 170-172] and measurement compatibility [38, 169] have come to researchers' attention and have been studied. Some other publications are focusing on feature selection, reliability and data treatment for forensic examiners [34, 37, 173, 174]. Articles of more technical nature treat device interoperability and verification performances [121, 148, 149, 172] on different devices and conditions. Data quality and examination reproducibility are increasingly important to researchers and practitioners.

There is also specific literature on examination and comparison methods in signature examination. Linden et al. propose an approach for defining a match based on whether or not its measured values are inside the variation observed from the known source signature sample [37]. Several authors have underlined how automation can help forensic examiners [130, 165, 166, 175-177]. Examination and analysis techniques for time-function features and parameter features have been used in biometrics and can be transposed to forensic science [39, 45, 150, 178-184].

Technical advances have been achieved in comparison techniques, using algorithms such as Longest Common Sub Sequence (LCSS) [181], Dynamic Time Warping (DTW) [30, 37], models such as Hidden Markov Models (HMM), Gaussian Mixture Models (GMM) or neural networks (NN) [30, 185], as support for the signature comparison process. New visualization tools and comparison procedures are being developed [34, 37, 186, 187]. Some commercial toolkits (e.g. Wacom Signature Scope, NeuroScript MovAlyzeR, signotec e-sig Analyze, Topaz SigAnalyze and SigCompare) are already available for forensic examiners, while others are under development by researchers [15, 188, 189]. These programs often offer extended visualization and analysis capabilities, helping the forensic examiner in his examination process. Unfortunately, dynamic signature data formats are often proprietary and no universally applicable open-source toolkit helping with data treatment, visualization and comparison currently exists.

While much progress has been made in data treatment, visualization, analysis and comparison, few authors propose ways to evaluate quantitative signature data probabilistically. Forensic science is undergoing a paradigm change [161, 162, 190-192], moving away from the uniqueness and individualization paradigm, distancing itself from categorical statements. The more recent probabilistic approach maintains that uncertainty is present in the inference process and should be handled with statistical tools and models. Recently recommended statistical evidence evaluation approaches rely on personal probability [193-196], the Bayes theorem [190, 195, 197-200] and to some extent decision theory [201-203]. Recommendations from European Institutes and American case law suggest that the Bayesian approach is more coherent and well adapted to forensic science purposes than categorical conclusions or purely technical information [161, 190, 191, 204-206].

Marquis et al. describe a static signature case, approached using the likelihood ratio approach and personal probabilities [207]. Gonzalez-Rodriguez et al. developed a way to use Likelihood Ratios in biometric systems, using Kernel Density Functions (KDF) [208]. Kupferschmid [187] also applies kernel density functions (KDF to either features or scores (obtained by DTW), and uses the estimated densities for Likelihood Ratio computation. Chen et al. [209] used a score-based (DTW) likelihood ratio framework to work on grayscale, width and radian information extracted from static signatures. Their approach is similar to Kupferschmid's, but they additionally measure calibration and performance of the system. Gaborini et al. [210] apply and adapt the method of Marquis et al., based on Fourier Descriptors [71, 211-214], and propose a multi-variate evidence evaluation approach.

As can be seen through the literature review in this article, dynamic signature examination has gained the attention of the forensic examiner community, which is actively working to fill methodological gaps and develop robust and reliable methods. This implies that there are still important steps to be taken to attain the demands set by documents such as the NAS [137] and PCAST reports [136]. Other forensic fields have already started adapting to the requirements set to forensic science by the legal system [215-217]. Forensic handwriting examination should also adapt, especially when dynamic signatures and quantitative data are involved.

Examiners should try to obtain information from digitizer manufacturers, to qualify measurement reliability and avoid detrimental pretreatment of data at the acquisition step. Standard testing procedures should be developed to test the measurement reproducibility of the digitizer and identify acquisition errors in the data. In this way, information about digitizer reliability data could be shared among laboratories. Research should also be directed at rational ways of selecting relevant and discriminating features in questioned signature cases. Using all available data contained in a dynamic signature is at best difficult and, at worst, detrimental to inference process. A robust way of selecting interesting and discriminating features for casework would greatly assist forensic examiners, who have to repeat the process for each new case. Multiple research teams should test comparison procedures for subjective visual inspection and automated comparison in order to qualify reproducibility. This would entail that a description of comparison methodologies always include mention of the data, procedure, algorithm and features that are being used.

Casework in forensic science is defined by many different circumstances. These circumstances may influence the dynamic features of signatures more strongly than the spatial characteristics. Ways to deal with particular parameters need to be found. Especially, temporal distance between questioned signatures and reference data introduces important variation in signature dynamics. Few studies with a focus on temporal distance's impact on dynamic features of signatures are known.

Most importantly, the scope of examination must be clearly defined. This calls for careful consideration of the court's needs. It would be desirable for examiners to clearly state their inference process and conclusion type, as well as to clarify the limitations associated with the chosen method [218]. Forensic examiners are invaluable in this process, as cases differ strongly and require adaptation to the case circumstances. Nevertheless, statistics and computer algorithms could be an invaluable asset to the Forensic Handwriting Examiner. They may not only strengthen reproducibility and transparency of the process, but also speed up examinations. Assumptions, data sets and procedures would have to be formulated clearly. Forensic signature examination has not, as of yet, adopted a probabilistic framework. The currently used method, mostly subjective assessment of graphical signature features, could be complemented with a statistical method dealing with the quantitative signature data. In this way, experts could make the most of the dynamic signature data, use the "best available evidence" and increase reproducibility and confidence in their results. The Bayesian framework for evidence evaluation would enable examiners to formalize a logically coherent reasoning process. Additionally, the Bayesian framework would give handwriting examiners a common vocabulary to express strength of evidence. This would facilitate exchange between researchers and colleagues, making collaborative testing and proficiency tests more easily comparable. Additionally, by conforming to the ENFSI and AFSP recommendations [163, 164, 218], the handwriting examiner guarantees adherence to quality standard and reduces exposure to criticism.

It is the authors' firm belief that research into these key aspects would greatly benefit the dynamic signature examination by increasing scientific and statistical rigor. This will hopefully lead to acceptance and recognition of forensic handwriting examination as valid scientific discipline and satisfy critics by providing both a structured approach and empirical data to back up the field's claims.

5. Conclusion

A state of the art of the forensic examination of dynamic signatures has been provided. The review focused on literature discussing dynamic features and their variation under multiple parameters, such as writing position, writing substrate, age or intoxication. It also provides a review of methodology for forensic dynamic signature examination, while pointing out gaps existing in the current way of evaluating findings.

The review has shown that case circumstances may have strong effects on both graphical and dynamic signature features. A lack of awareness about these parameters may lead to overestimation (or underestimation) of signature variation. In mild cases, this may lead to unjustified confidence in results, while in the worst case this may lead to erroneous conclusions. The state of the art has shown that valuable information on dynamic features in signatures can be found. While technical and signature variation related knowledge continually appears, few studies deal with forensic evidence evaluation and inference. Evett [190] reminds forensic practitioners that forensic science is about reasoning, not only about technical advancement and empirical data. The technical studies provide the construction materials for good forensic science, but without a solid foundation in the form of a framework for reasoning, the conclusion cannot remain standing.

Researchers should continue exploring dynamic data and its variation. Nevertheless, forensic scientists should not forget that empirical data is given meaning through an evaluation process, which necessitates a framework, method and statistical model for reasoning. The next step for forensic examination of dynamic signatures will be the development of a probabilistic model that is able to use empirical data to inform the Bayes Factor. This model will support the forensic examiners in their casework through reliable and reproducible inference.

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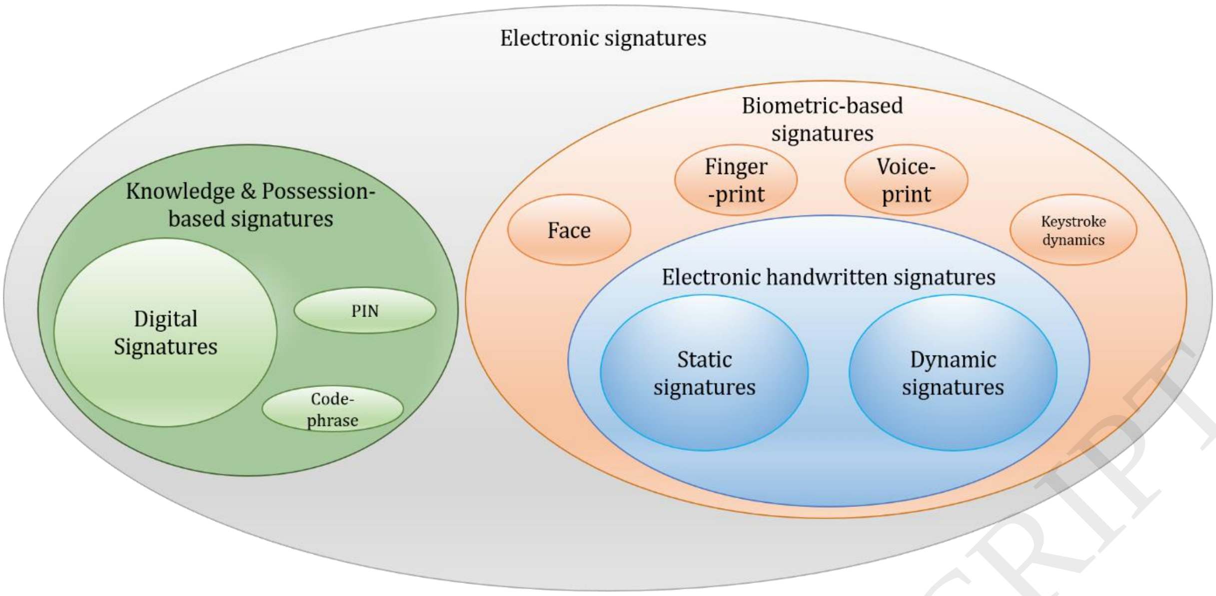

Figure 1 - Taxonomy of electronic signatures

Table 1 - Summary of terminology

TERMINOLOGY	SYNONYM	DESCRIPTION
PHYSICAL SIGNATURE	Signature, 'pen and paper' signature	The ink trace resulting from the recording of the signature movements on a physical substrate, such as paper
ELECTRONIC SIGNATURE	None	The 'electronic proof of a person's identity' [19] For further definitions see [20-22] Global category, designates all kinds of 'electronic' data providing proof of authenticity.
DIGITAL SIGNATURE	Cryptographic signature	The 'electronic proof of a person's identity involving the use of encryption; used to authenticate documents [23]
HANDWRITTEN ELECTRONIC SIGNATURE	None	Specific category, designates handwritten signatures containing only graphical data (static) or including temporal and movement data (dynamic)
STATIC SIGNATURE	Off-line signature	Digitalized version of a handwritten signature containing only graphical information (e.g. scanned signatures, image file of dynamic signatures)
DYNAMIC SIGNATURE	Online signature	Digitalized version of the signature movement signal. Chronological list of data points

Table 2 - Linkage between quantitative dynamic features and qualitative features used by FHEs

DYNAMIC FEATURE	RELATED FHE FEATURE
TIMING	None
POSITIONAL DERIVATIVES (SPEED, ACCELERATION, JERK)	Tapering, flying starts & ends, line quality, fluidity & tremor, ink quantity, line width
PRESSURE	Shading, relative pressure, ink quantity, line width
PEN ANGLES (TILT, ALTITUDE, AZIMUTH)	Shading
IN-AIR FEATURES	None

Table 3 - Parameter effect on handwriting

PARAMETER	MAIN EFFECT	SIDE EFFECTS	SUMMARY
AGE	Increase in time and decrease in writing speed	Decrease in fluidity	Aging effects strongly depend on the individual and affect dynamics differently. Age group differences have been observed.
HEALTH	Depends on condition	Depends on condition	Diversity in diseases and effects is enormous. Effects range from movement planning disruption to effector problems. Specific literature on the condition needs to be consulted.
POSTURE	No notable effects	No notable effects	Existing studies have been unable to show significant changes due to posture.
FATIGUE	No notable effects	Increased spacing	Effects are only observed in tasks requiring concentration for long amounts of time. Signatures are not affected.
ALCOHOL	Increase in writing speed and acceleration, increase in variation of dynamic features, imbalances in dynamics	Diverse effects depending on dose and individual	Alcohol has strong effects on dynamics, but the effect strength depends on time of consumption and quantity ingested.
INTOXICATION	Dependent on substance type, dose administered and metabolizing	Dependent on substance type, dose administered and metabolizing	Effects are diverse due to the diversity in substances and effects on the brain and effectors.
WRITING SURFACE ROUGHNESS	No notable effects	Smooth surfaces may cause higher writing speed and higher pressure.	Effects appear mainly while becoming accustomed to the tablet or in comparison with writing on paper.
WRITING SURFACE ANGLE	Various effects in extreme cases (vertical surface).	No notable effects	Only extreme changes, like vertical surfaces (walls), force a change in effectors and produce notable changes.
WRITING SURFACE SIZE	Dependent on the individual, may reduce speed and shrink writing to fit	Pressure is affected very little by constraint	Type of constraint and severity of not respecting constraints may be important. Effect highly depends on the individual's choice and adaptation to the constraint.
WRITING INSTRUMENT	Higher variation in graphical and dynamic features when using a writing implement the person is not used to (e.g. finger)	No notable effects	Signing with a finger rather than a pen with nibs introduces more variation. Effect strength depends on interaction between writing surface and writing instruments.