

# Some Observations on Handwriting from a Motor Learning Perspective

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**Abstract**—We discuss the dynamics of signatures in the light of recent findings in motor learning, according to which a signature is a highly automated motor task and, as such, it is stored in the brain as both a trajectory plan and a motor plan. We then conjecture that such a stored representation does not necessarily include the entire signature, but can be limited to only parts of it, those that have been learned better and therefore are executed more automatically than others. Because these regions are executed more automatically than others, they are less prone to significant variations depending on the actual writing conditions, and therefore should represent better than other regions the distinctive features of signatures. To support our conjecture, we report and discuss the results of experiments conducted by using an algorithm for finding those regions in the signature ink and eventually using them for automatic signature verification.

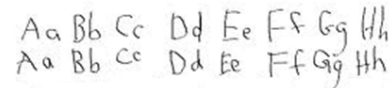
**Index Terms**—motor learning and execution; stability region; signature verification;

## I. INTRODUCTION

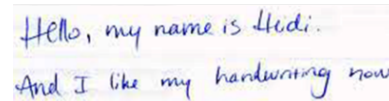
According to the daily experience, a coordinated sequence of "elementary" movements is acquired and executed faster and more accurately the more it is practiced. Early in learning, actions are attention demanding, slow and less accurate, whereas after long-term practice performance becomes quick, movements are smooth, automatic, and can be performed effortlessly, using minimal cognitive resources.

Studies on motor control have shown that selection, execution and learning of the movements needed to perform a motor task involve several brain areas and motor subsystems, but their activation and cooperation depend on the kind of movements that are being made and on the effector that is being used [1].

Indeed, when a child starts learning handwriting by copying letters or words, he attempts several trajectory patterns in order to replicate the same shape of the letters, selecting the points to reach through the visual system, and performing the appropriate sequence of movements through the motor system. During the initial phase of learning, the movements are quite straight and aimed to reach a sequence of points (as in Figure 1a). The executed motor plan is corrected according to the information provided by the visual and proprioceptive feedback, so that the actual trajectory corresponds to the desired one, and the lowest energy is spent by the muscular subsystem involved. As learning proceed, simple point-to-point movements become continuous, curved and smoother,



(a)



(b)

Fig. 1. Handwriting samples, written by a child (a) and a skilled writer (b).

the motor sequence comes to be executed as a single behavior and is performed automatically, using minimal cognitive resources (as in Figure 1b).

There is also strong evidence, supported by the results of several experimental studies on motor learning, that a given sequence of actions is learned from different perspectives. It has been observed, first by Lashley [2] and then by Hebb [3], that a generic movement, learned with one extremity, can be executed by different effectors. Furthermore, other studies have shown that writing movements learned through the dominant hand could be repeated using different body parts, such as non-dominant hand, the mouth (with the pen gripped by teeth) and foot (with the pen attached to it), even if the subject had essentially no previous experience writing with any of this body parts [4], [5]. Despite the different muscular and skeletal systems used and, even though the movements are not smooth, it can be observed that the writing production follows the same trajectory in all conditions [4] (see Figure 2). The ability to perform the same movement pattern by different muscular systems is called "motor equivalence". It suggests that movements directed to perform a task are stored in the brain in two ways: in an abstract form (effector-independent) related to the spatial sequence of points representing the trajectory plan, and as a sequence of motor commands (effector-dependent) directed to obtain particular muscular contractions and articulatory movements.

Other studies on motor learning have shown that when the untrained hand is used to perform a given sequence, learned with long-term practice with the other hand, performances are poor, but this is not true for a newly learned sequence [6],

supporting the hypothesis that early in learning the execution of the motor task is more based upon the trajectory plan (effector independent), whereas late in learning upon the sequence of motor commands (effector-dependent).

Execution of voluntary movements requires the interaction between nervous and musculoskeletal systems, involving several areas, from the higher cortical centers to the motor circuits in the spinal cord [7].

In seeking to understand all the breadth and facets of motor learning, many researchers have used different approaches and methods, such as genetic analysis, neuroimaging techniques (such as fMRI, PET and EEG), animal models and clinical treatments (e.g. drugs administration and brain stimulation). These studies have provided a large body of knowledge that has led to several theories related to the role of the central nervous system in controlling and learning simple and complex movements. According to the results reported by neuroimaging and experimental studies on motor learning, several cortical and subcortical structures, including the basal ganglia, cerebellum, and motor cortical regions, are thought to be critical in different stages and aspects in the acquisition and/or retention of skilled motor behaviors.

In order to locate which brain area, or areas, underlie effector-independent representation of handwriting, Rijntjes and colleagues [8] carried out an fMRI study to examine patterns of brain activation associated with signing, using either the hand or the big toe. Their results showed the involvement of the parietal cortex in general, and posterior parietal cortex and occipitotemporal junction in particular, in the representation of written letter forms.

More recently, other neuroimaging studies have investigated the dynamics and functional connectivity of brain networks associated with learning a novel sequence of hand stroke movements to write ideomotor character [9]. Their results also suggest that a novel sequence of movements is initially mapped to form an internal representation of the sequence that is progressively encoded and refined subcortically (in the basal ganglia and in the cerebellum) as performance improves.

The imaging data reported by other studies on motor learning support the notion that distinct regions of the basal ganglia participate in different stages of learning. These studies report increased activity within the striatum (the input nucleus of the basal ganglia), in particular within the associative striatum and sensorimotor striatum early and late in learning, respectively. However, although there is solid evidence that the initial learning of many skills depends on the striatum, there are contrasting results in the literature regarding to the role of the sensorimotor striatum in automatic responding. For example, whereas some fMRI studies reported increased activity in the sensorimotor striatum with extended training, others reported decreased activity. Moreover, Turner and colleagues [10] reported that temporary inactivations of sensorimotor regions of the internal segment of the globus pallidus (a basal ganglia nucleus whose activity depends on the sensorimotor striatum) did not impair the ability of monkeys to produce previously learned motor sequences. Therefore, these results

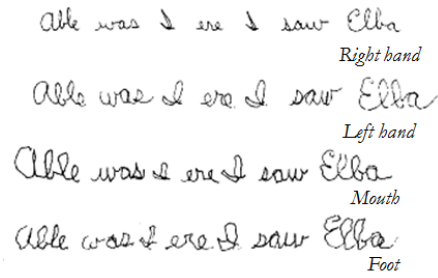


Fig. 2. A sentence written by the same writer using different body parts. Reproduced from [4].

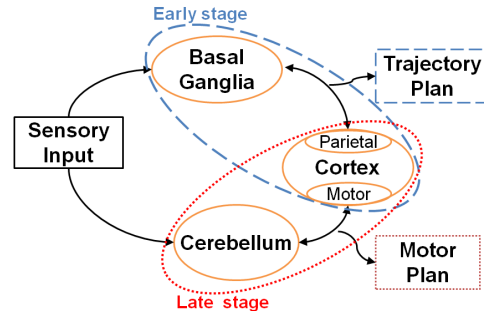


Fig. 3. Neural scheme of the model for procedural motor learning.

sustain the hypothesis that the basal ganglia play an important role in the initial stage of learning, whereas it is not well-established their importance in the final stage of learning.

With regard to the cerebellum, many studies report increased activity within the cerebellar cortex during learning, and increased activity within the dentate nucleus (an output nucleus of the cerebellar circuitry) until automaticity is achieved. A detailed review of the imaging studies whose results are here cited can be found in [11].

According to these results, we have proposed a neural scheme, based on the hypothesis that acquiring new motor skills requires two phases, in which two different processes occur:

- during the early stage, humans learn the spatial sequence associated to the motor task in visual coordinates, i.e. the sequence of points to reach in order to generate the ink trace.
- during the late, automatic phase, the sequence of motor commands in motor coordinates is acquired and comes to be executed as a single behavior.

The neural scheme for motor learning is shown in Figure 3 and incorporates the parietal and motor cortex, basal ganglia and cerebellum [12].

Sensory information is provided by an input module (sensory input in the figure) to the cerebral cortex, basal ganglia and cerebellum. The parietal association cortex releases signals that specify the position of targets in extrapersonal space (according to the studies conducted by Andersen and Zipser [13] and Rijntjes [8]). Therefore, the basal ganglia, interacting

with the parietal cortex, select the next target point in the sequence. In turn, parietal cortex sends this information to the cerebellum that, interacting with the motor cortex, selects the appropriate motor command.

This model fits with the our hypothesis that motor learning follows two distinct phases. During the early phase of learning, the model learns the spatial sequence in visual coordinates (i.e. the sequence of points to reach in order to realize the motor task) through the interactions between the basal ganglia and the parietal cortex. The spatial sequence is then converted into motor commands through the interactions of the cerebellum and the motor cortex. Therefore the cerebral cortex, basal ganglia and cerebellum initially would work in parallel. The basal ganglia, through the associative striatum, are involved in the acquisition of the spatial sequence and the cerebellar cortex starts working to acquire the motor sequence. As learning proceeds, the sequence of motor commands in motor coordinates is acquired and stored in the dentate nucleus.

## II. SIGNATURES AND MOTOR LEARNING

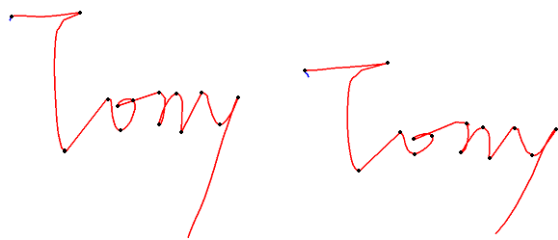
The neural scheme illustrated in the previous section suggests that after the learning, i.e. when the movement is executed fluently, the sequence of motor command is executed as a single movement. It suggests also that the more a movement is repeated the better is learned, i.e. the more it is automated. When applied to handwriting, the model suggests that the ultimate goal of the learning is that of producing a repertoire of completely automated movements in correspondence of the most frequently used sequences of characters. Such a repertoire depends on the sequences of characters the writer is most familiar with, which triggers the learning, and the sequences of the corresponding motor commands. Thus, the handwriting style emerges from both those aspects, the former being mainly language and cultural dependent, the latter being dependent on the physical and cognitive motor skills of the subject. Accordingly, different subjects may develop different repertoires of completely automated movements, either because the sequences of characters for which a completed automated movement is learned are different or because a different sequences of motor commands are learned for a given sequence of characters. When a completely automated movement has been learned for an entire message, multiple executions of such a movement should produce similar results, the difference between them being mainly influenced by the effector-dependent encoding of the learned sequence rather than from the effector-independent one. On the other hand, when more than one completely automated movement needs to be used for encoding the entire message, further variability may be observed in multiple execution of the same movements because the movements introduced for smoothing the transition between two successive completely automated movements are planned on the fly during the execution, and therefore may vary in both the effector-independent and the effector-dependent component.

What do these observations suggest in case of signatures? A signature is a movement the subject is very familiar with,

that has been learned through repeated practice, and therefore it will have triggered a learning process whose final result is the repertoire of completely automated movements used by the subject while signing. If the entire signature is encoded in a single completely automated movement, it is expected that signatures produced by using the effector under the same condition result in very similar traces. In such a condition, in fact, the effector-independent part of the movement does not change because it has been completely learned and the effector-dependent component is supposed to be the same during all the execution. On the contrary, if the signature is produced by executing more than one completely automated movement, repeated execution may produce different traces, even under the assumption that the effector is used under the same condition, because there will be differences in the movements, and therefore in the traces, for connecting two successive completely automated movements. It follows from the observations reported above that whatever (dis)similarity measure is adopted for deciding whether a signature is genuine or not, it should be handled with care. In particular, it can be used successfully only after it has been decided which one are the parts of the signature that correspond to the execution of completely automated movements, and only the (dis)similarity between those parts of the signatures at hand should be evaluated by the adopted measure, because only those parts are expected to be "stable" across multiple executions of the signature. In other words, the signature verification should be conducted by weighting differently the (dis)similarity between "stable" regions and the (dis)similarity between other regions of the signature. In the following sections, we will briefly illustrate a procedure we have designed for finding the stability regions and then results obtained in a signature verification experiment.

## III. FINDING THE STABILITY REGIONS

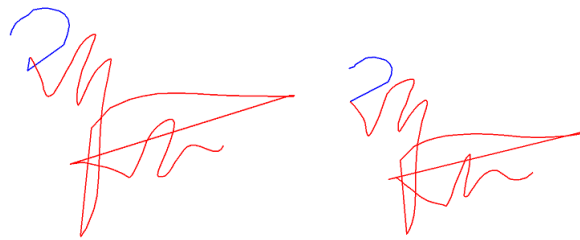
It follows from our definition of stability regions that they are sequences of strokes produced as a single behavior and therefore should be embedded into any execution of the signature. Let us recall that a completely learned movement is stored in two forms, a sequence of target points, and a sequence of motor commands, and that the former is effector-independent, while the latter is effector-dependent. When the same effector is used in multiple executions, therefore, the only source of variability is the actual state of the effector, which may give raise to local variations in the shape of the ink traces. These traces, however, are composed of the same number of strokes and aimed at reaching the same sequence of target points. Assuming such a perspective, the stability regions are the longest common sequences of similar strokes found in two signatures, where similar means that they are aimed at reaching the same sequence of target points by following the same path. The method we have developed for finding the stability regions assumes that the signature signal has been segmented into a sequence of strokes, and the detection of the stability regions is achieved by an ink matcher that finds the longest common sequences of strokes with similar shapes between the inks of



(a) Genuine n. 16

(b) Genuine n. 19

Fig. 4. Genuine signatures produced by the user n. 22. The stability region is in red.



(a) Genuine n. 8

(b) Genuine n. 10

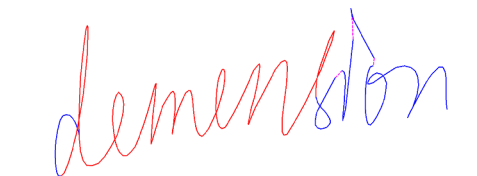
Fig. 5. Genuine signatures produced by the user n. 40. The stability region is in red.

a pair of signatures [14]. For deciding when two sequences are similar enough, i.e. when they match, the method exploits the concept of saliency that has been proposed to account for attentional gaze shift in primate visual system [15]. The rationale behind this choice is that, by evaluating the similarity at different scales and then combining this information across the scales, sequence of strokes that are globally more similar than other will stand out in the saliency map. The global nature of the saliency guarantees that its map provides more reliable estimation of trace similarity with respect to that provided by local criteria, as it is usually proposed in the literature [16]. According to the definition of stability regions, one would expect that the sequences of similar strokes provided by the ink matching appear in all the signatures. In practice, however, both the stroke segmentation and the ink matching may introduce errors, in locating the segmentation points (i.e. estimating the trajectory) and/or deciding when a sequence of strokes is similar to another (i.e. estimating the motor plan), that may produce different stability regions for the set of signatures. To decide which sequences correspond to the stability regions, we consider that longer stability region correspond to longer sequence of elementary movements executed in a highly automated fashion. Because the level of automation is the result of the learning process described above, and because the learning is an individual feature, long stability regions are more subject specific than short ones. Accordingly, we remove the stability regions that are subsequences of longer ones.

#### IV. EXPERIMENTAL RESULTS

We have two experimental results to support our conjecture about the role of stability regions in signature learning and execution and their effectiveness in signature verification. In both cases, the experiments were conducted on the SVC2004 dataset, adopted in the literature for writer verification/identification [17].

The first one was carried on by 3 subjects independently. They were provided with a written definition of stability regions in terms of sequence of strokes and asked to find them between 100 pairs of genuine signatures previously segmented by our algorithm. We then compared their outputs and removed 13 pairs for which there was some disagreement among them. This 87 pairs were then processed as above and the provided output compared with the one provided by the experts. In all the cases we have found a perfect correspon-



(a) Genuine n. 14



(b) Genuine n. 18

Fig. 6. Genuine signatures produced by the user n. 6. The stability region is in red, the pen-up in magenta.

dence between the machine and the expert. As an illustration of the results, the figures 4-6 show the stability regions found by the algorithm in case of signatures of different complexity. Figure 4 shows two signatures produced without any pen-up and pen-down occurring between the beginning and the end of the signature. The two traces are divided into the same number of strokes, and the stroke segmentation points, represented in figure as black dot, are located on the shape so as to roughly preserve their relative positions. According to our model, thus, the subjects concluded that the two shapes have been generated by the same motor plan, because it aims at reaching the same sequence of target points (estimated by the relative position of the segmentation points, as described in [18]) by means of the same sequence of elementary movements with the same time superimposition between successive ones (as estimated by the similarity between sequence of strokes). In this case, one would expect the algorithm to find just one stability region covering the whole signature, as it happens. Figure 5 shows two signatures produced by another writer without lifting the pen, as in the previous case, but with the end-effector in a different initial condition. Again, by looking at the segmentation points and at the similarity between sequence of strokes, the experts (and the machine as well) concluded that there was a difference in the initial parts of the signature (depicted in blue in the figure) and therefore they were not include in the stability region. Eventually, figure 6 depicts two long and complex signatures produced by a third writer.

Because of the pen-up within the trace, depicted in magenta, and according to our conjecture, we expect that this signature is less automated and that stability regions may be found only during pen-down, as it happens. When requested to explain why they did not include the beginning of the ink trace (in blue) in the stability regions, the experts told us that the movement at the beginning of the sequence were very different, since in the first case the first stroke was directed top left, while in the second it was directed to left, showing also a sign of hesitation at the very beginning, as the subject started a movement directed down-left and suddenly corrected it. Similarly, in the first case it appears to be a stop-and-go or an hesitation while drawing the letters. In both cases, they were interpreted as sign of difference between the sequence of strokes constituting the motor plan.

The second result comes from a signature verification experiment we have designed and performed on the same dataset [14]. In such an experiment, we have used the stability regions provided by our algorithm for both selecting the genuine signatures to be used as reference and classifying the questioned signatures as both genuine or forged. Each questioned signature was compared with the stability regions of the references. If a match was found, the similarity between the sequence(s) of strokes of the stability region(s) in the reference and the matching sequences of strokes in the questioned was compared with two thresholds, to decide whether the questioned was genuine or not. Despite this very simple decision criteria, and the exploitation of shape information only for measuring the similarity between sequence of strokes, the experimental results showed that our method was the 5th among the 15 methods considered in the final ranking, but also that it exhibited the lowest standard deviation of the performance. This latter finding suggests that the method captures the common aspects of signatures as they derive from the model, and therefore is quite robust in providing similar performance independently of the distinctive signing habit of each subject. Even more interesting, most of the errors are found in case of signatures with many pen-up and pen-down, and whose stability regions are made of a few strokes, further supporting our claim that the more the signature is automated the longer are the stability regions.

All together, those results show that stability regions, as we have defined and implemented them, do seem to exist and that they can represent a promising way to root signature verification within the framework of motor learning and execution.

## V. CONCLUSIONS AND FUTURE DIRECTIONS

We have discussed some recent findings in neurocomputational modeling of motor learning and execution and suggested that they may provide a new perspective for handwriting analysis. Under such a perspective, we have conjectured that signatures are represented as a motor plan, stored in a distributed fashion between the basal ganglia and the cerebellum, which encodes both the target points to be reached and the motor program to execute for producing the desired handwriting. From this conjecture we have derived a definition of stability

regions by globally evaluating the traces shape similarity by means of a saliency map.

Our conjecture is supported by two experiments showing that: human subjects may actually find stability regions that fits with our definition and that such regions provide a plausible estimate of the motor plans used to produce the observed traces; the proposed algorithm finds the same stability regions as the human subjects; the stability regions may be used for both selecting the reference signature and performing signature verification, providing very promising results even when a very simple criterion is used to decide whether a questioned signature is genuine or not.

In the future we will investigate to which extent our model can deal with disguising writers. We would also like to understand whether there is any relation between legibility and learning of signatures.

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