Should We Look at Curvature or Velocity to Extract a Motor Program?

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Abstract. Experimental studies led by Lashley and Raibert in the early phase of human movement science highlighted the phenomenon of motor equivalence, according to which complex movements are represented in the brain abstractly, in a way that is independent of the effector used for the execution of the movement. This abstract representation is known as motor program and it defines the temporal sequence of target points the effector has to move towards to accomplish the desired movement. We present and compare two algorithms for the extraction of motor programs from handwriting samples. One algorithm considers that log-normal velocity profiles are an invariant characteristic of reaching movements and it identifies the position of the target points by analysing the velocity profile of samples. The other algorithm seeks target points by identifying the trajectory points corresponding to maximum curvature variations because experimental studies have shown that the activity of the primary motor cortex encodes the direction of the movement. We have compared the performance of the two algorithms in terms of the number of virtual target points extracted by handwriting samples generated by 32 subjects with their dominant and non-dominant hands. The results have shown that the two algorithms show a similar performance over ∼55% of samples but the extraction of motor programs by analysing the curvature variations is more robust to noise and unmodeled motor variability.

Keywords: Motor equivalence · Motor program extraction · Handwriting representation

1 Introduction

The analysis of movement, as the analysis of gait or handwriting, is the core of many tools used for biometric [6,7,17,18,24] and diagnostic [2–4,20] purposes. That is because complex movements are the result of a learning process that is individual and neurodegenerative disorders, like Parkinson's and Alzheimer's disease, affect motor skill learning, execution and retention.

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Being able to infer the representations of movements acquired by learning and stored in the brain is of paramount importance because it allows to distinctively identify a person or to monitor the onset and the progression of neurodegenerative diseases.

The phenomenon named *motor equivalence* suggests that "*actions are encoded in the central nervous system in terms that are more abstract than commands to specific muscles*" [35]. This abstract representation is known as *motor program*, which has been also defined as "*a central representation of a sequence of motor actions*" [28]. Therefore, a motor program is an effector-independent representation of the movement that is made up of a sequence of target points that have to be reached in order to execute the desired movement. To a motor program may correspond more than one effector-dependent representation of the movement, each of which encodes the motor commands that will be delivered to the specific neuromuscular system recruited for the execution of the movement [14,25].

Different algorithms have been proposed for extracting the motor program from a trajectory, i.e. to identify within a handwriting movement the elementary movements, from here on named strokes, it is made up of [8,12,13,16,19]. Because variations in the writing conditions and in the psychophysical state of a subject influence the execution of a complex movement, we can observe differences in the motor programs extracted from different executions of the same trajectory. Differences can be observed in the number of extracted strokes, in the parameter values used for representing strokes and in the x-y position of target points.

We present and compare two algorithms for the extraction of motor programs from handwriting samples; one defines the position and the number of the target points from the analysis of the velocity profile, while the other finds the target points by looking at the variation of curvature along the trajectory. Because, by definition, a motor program is independent of the variability affecting different executions of the same drawing or word, we compared the two algorithms in terms of the number of strokes extracted from each sample. The desired outcome is the extraction of the same motor program from any repetition of the same learned movement.

The remaining of the paper is structured as follows: Sect. 2 describes the two algorithms and the theoretical framework within which they were conceived, Sect. 3 describes data collection and the experimental procedure, and it reports the results that are then discussed in Sect. 4. Eventually, Sect. 5 concludes the work by discussing further investigations of this preliminary work.

2 Method

2.1 Theoretical Overview

The repetition of a complex movement over time has the effect of creating a compact representation of the movement that, in the final stages of learning, is stored in the brain as a succession of target points that have to be reached.

The execution of a learned movement, i.e. the realization of a motor program, results from the interaction between brain areas, spinal cord networks, muscles and the proprioceptive receptors [21,27]. In a nutshell, to initiate the movement, the brain sends commands to recruit the muscles and to set the forces they have to exert on the bones they are connected to, while, during execution, the spinal cord modulates such commands depending on the information received by the proprioceptive receptors in order to keep the execution as close as possible to the learned one. The effects of those modulations are therefore the source of the observed variability, and they should not be considered as the results of commands stored in the motor plan.

The active role of the spinal cord in the control of movements became clear with studies on spinal cord plasticity and spinal stretch reflexes. Studies have shown that spinal cord plasticity contributes to the acquisition of motor skills, and to compensation for the peripheral and central changes caused by ageing, disease, and trauma [36]. More recently, it has been proved that spinal feedback pathway is able to integrate proprioceptive inputs from multiple muscles to produce efficient corrective responses that take advantage of musculoskeletal redundancy [34].

Thus, after a movement has been learned, i.e. when the subject executing the movement is no longer conscious of the elementary movements it is composed of, the variability observed in repeated executions may be ascribed to the neuromuscular system executing the movement. Extracting the motor program by observing the execution of a complex movement requires to be able to identify those corrective movements introduced on the fly by spinal cord networks.

In the next subsection, we introduce two algorithms for the extraction of motor programs, MPE and CMMPE. Both the algorithms adopt the lognormal representation of handwriting movements derived from the kinematic theory of rapid human movement [22]. Therefore, each elementary movement is characterized by a lognormal velocity profile and it is described in terms of command generation time, magnitude and direction of motion, response time and time delay of the neuromuscular system [23]. The two algorithms were designed starting from different but complementary findings in the field of motor control and, therefore, they differ in the way they seek movements embedded in the motor program.

MPE seeks for strokes by looking at the velocity profile of a sample. This choice follows from the experimental evidence that reaching movements show some stereotypical properties like a roughly straight path and, more importantly, a velocity profile with a dominant slightly asymmetric peak [15,23]. Therefore, MPE identifies strokes in a sample by positioning lognormal functions at the more significant peaks of the velocity profile.

CMMPE seeks for strokes by looking at the curvature variation along the trajectory of samples. Experimental studies have shown that neural activity in the primary motor cortex is related to movement direction that is uniquely predicted by the action of a population of motor cortical neurons [9]. Therefore, CMMPE seeks for strokes by detecting the points of the trajectory where there is the maximum variation of curvature because at those points the change of direction in the movement is evident and significant and, therefore, it is more plausible that it is the effect of a central command than of a corrective movement.

2.2 Motor Program Extraction

MPE. The Motor Program Extractor algorithm, hereinafter MPE, analyzes velocity profiles to recover the sequence of virtual target points the motor commands issued by the brain intended to reach. The fundamental idea behind this algorithm is that both the brain and spinal cord contribute to the final movement by generating elementary movements with a lognormal velocity profile. Movements commanded by brain areas are those encoded in the motor program, while the spinal cord contributes with fast corrective movements by integrating commands from brain areas and proprioceptive signals. Movements introduced by the spinal cord are generated when the ongoing movement is going far from the intended/planned movement. MPE extracts the motor program from one handwriting sample by detecting and discarding the corrective movements introduced by the spinal cord.

MPE adopts the same iterative procedure proposed by the RX0 algorithm [16] to extract elementary movements by the analysis of the velocity profile and models each elementary movement with the Sigma-Lognormal model [23]. At each iteration, the velocity profile of a handwriting sample is analyzed searching for peaks. A movement generated by the spinal cord should correspond to either a velocity peak whose amplitude is much smaller than the amplitudes of the velocity peaks related to movements encoded in the motor plan, or whose duration is shorter than the duration of the movements defined by the motor plan. Therefore, the amplitude and the duration of each peak are compared with two thresholds, denoted by V_{th} and T_{th}, respectively, and peaks whose amplitude or duration are lower than the respective threshold are ignored. A detailed description of the algorithm and its validation on a data set different by the one adopted in this paper is available at [19].

CMMPE. The Curvature Multiscale Motor Program Extractor, hereinafter CMMPE, analyzes curvature profiles to estimate the position of the virtual target points the motor commands issued by the brain intended to reach. The fundamental idea behind this algorithm is that the amount of time superimposition between two consecutive elementary movements regulates the smoothness, and therefore the curvature, of the trajectory. If the second elementary movement starts when the first one is ended, the virtual target is visible in the actual trajectory, while it disappears when the second movement starts before the end of the previous movement. The region of the trajectory where the maximum curvature variation is measurable defines the region external to the trajectory where the virtual target point may be located, as shown in Fig. 1.

CMMPE detects the points corresponding to the maximum curvature variation, from here on segmentation points, by exploiting an algorithm based on the

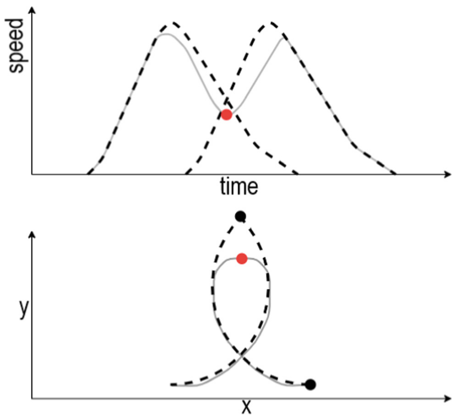

Fig. 1. Example of segmentation point (red dot) in a trace composed of two time-superimposed strokes (grey line). The dashed black line represents the strokes if no superimposition was applied, and the black dots are the virtual targets. (Color figure online)

concept of saliency introduced for modelling visual attention shift [5]. Following this approach, the trajectory represents the scene the system is looking at, and its curvature represents the feature whose saliency is estimated. Curvature is computed at different resolutions and then values at each scale are combined in order to estimate a saliency map S_{MAP}. Thus, the algorithm carries out a saliency-based multiscale analysis of the curvature profile and the values of the saliency map higher than a threshold S_{th} correspond to the segmentation points. The detection of segmentation points is much more invariant with respect to locally prominent but globally non-significant changes of curvature, which means it is able to filter the local variation of curvature introduced by corrective movements. The threshold S_{th} depends on the parameters w and α as defined by Eq. 1:

$$S_{th} = \text{average}(\text{moving\_mean}(S_{MAP}, w)) * \alpha \tag{1}$$

where w defines the length of the moving mean, while α modulates the mean saliency.

CMMPE assumes that a virtual target point is located along the line perpendicular to the tangent to the trajectory at the segmentation point. Even this algorithm models each elementary movement with the Sigma-Lognormal model but, differently from MPE and other algorithms proposed in the literature, it first analyses the trajectory to locate the position of a target point and then it computes the lognormal velocity profile related to the elementary movement that reaches the target point.

Fig. 2. Trajectory reproduced by each subject involved in the experimentation.

3 Experimentation

3.1 Data Collection

We collected data from 32 subjects, 18 males and 14 females, whose age ranges in the interval 13–63 years with a mean value of 34.40 and a standard deviation of 15.58. Participants volunteered to take part in the experiment and expressed their written informed consent to participate. We administered a questionnaire to each subject in order to define their level of education, health conditions and whether they use routinely drugs or other substances that are known to affect motor control.

Each subject wrote the handwriting pattern "llll", whose template is shown in Fig. 2, 10 times with his/her dominant hand and then 10 times with his/her non-dominant hand. This pattern has been adopted in many experiments on handwriting generation modelling [29,30,32] because it is reasonable to assume that its motor program has been already learned by the subjects involved in the experiments and it is complex enough to evaluate how motor variability and motor noise affect the execution of a planned motor program.

We collected samples drawn with both hands to verify our hypothesis that the number and the position of target points are less stable among different repetitions when movements are executed with non-dominant hands. That is because each subject will try to execute the trajectory by the non-dominant hand by reaching the sequence of target points encoded in the learned motor program even though the sequence of motor commands to control the new effector is not yet learned. As a consequence, a stronger intervention of spinal and supraspinal neural networks will be triggered and a greater variability among the samples, as well as among the extracted motor programs, will be evident.

Overall, we collected 320 handwriting samples drawn with dominant hands and as many samples drawn with the non-dominant hands. The handwriting samples were collected by using an ink-and-paper WACOM Bamboo Folio digitizing tablet with 200 Hz sampling rate. We developed a custom application to acquire and store each sample.

We adopted an ink-and-paper digitizing tablet to avoid unexpected proprioceptive feedback and the following corrective movements that may arise by using a stylus-and-screen digitizing tablet. In fact, it has been shown that handwriting is influenced by the lower friction of tablet surfaces in a way that subjects are required to additionally control handwriting movements [10].

3.2 Experimental Procedure

The experimentation aims at comparing the two algorithms in terms of the number of strokes, i.e. the number of virtual target points, extracted from the handwriting samples. This is because the handwriting samples produced by each subject should be the execution of the same motor program and, therefore, they should be made up of the same number of strokes.

Both MPE and CMMPE require to set a couple of parameters, (V_{th}, T_{th}) and (w, α), respectively. V_{th} and T_{th} define the amplitude and duration of a corrective movement generated by the spinal cord networks. w and α regulate the minimum variation of curvature that is considered as the effect of a new motor command issued by the brain instead of a corrective movement introduced by the spinal cord. In both cases, the parameters define the boundary between corrective and planned movements.

Studies in literature have shown that activity-dependent plasticity occurs in the spinal cord as well as in the brain [31,36] and that spinal cord plasticity is important in the acquisition of motor behaviours throughout life [37]. For example, it has been shown that athletic training, such as that undertaken by ballet dancers, gradually alters spinal reflexes [37,38]. Therefore, it is plausible to assume that the extent of corrective movements introduced by the spinal cord varies subject by subject.

Therefore, both for MPE and CMMPE, we tuned the parameters per each subject to characterize their personal spinal cord activity. In particular, starting from the assumption that executions of the pattern "llll" with the dominant hand are the actuation of the same motor program, we set the parameters at values that produced the minimal variation in terms of the number of extracted strokes from the ten repetitions. For both algorithms, we adopted a grid search approach to set the parameter values. For MPE, V_{th} was varied between 10% to 60% of the maximum velocity peak measured in the sample under analysis, T_{th} was varied between 20 ms and 90 ms because voluntary movements toward a target are usually executed in a time range that varies between $\sim$350 ms and $\sim$1200 ms, depending on the subject [33]. For CMMPE, w was varied between 1 and 5 and α between 0.6 and 1 with a step of 0.2. These two ranges were defined by a preliminary analysis carried out on another data set [18,19].

Given a subject, the parameter values tuned on the samples drawn with the dominant hand are used to extract strokes from the ten samples executed with the non-dominant hand.

3.3 Results

Table 1 reports the mean number of strokes extracted by the two algorithms on the samples drawn with the dominant or non-dominant hand by the 32 subjects.

Figure 3 shows the distributions of the handwriting samples drawn with the dominant hand per number of strokes. We applied a two-sided Wilcoxon signed rank test to verify the null hypothesis that the difference between the distribution obtained with MPE and the one obtained with CMMPE has zero median. The

Table 1. Mean number of strokes (±standard deviation) per algorithm and per end-effector

	MPE	CMMPE
Dominant Hand	8.38 ± 0.62	8.03 ± 0.90
Non-dominant Hand	9.53 ± 1.75	9.10 ± 1.60

null hypothesis was rejected (*p-value* $= 2.43 * 10^{-10}$) and a right-tailed Wilcoxon signed rank test rejected the null hypothesis (*p-value* $= 1.23 * 10^{-10}$) in favour of the alternative hypothesis that the difference distribution has a median greater than 0, i.e. MPE extracts more strokes than CMMPE. Figure 4 shows that when the same sample is elaborated by the two algorithms the same number of strokes were extracted 221 times out of 320 (∼69%). For 58 out of 320 samples (∼18%) the motor programs extracted by MPE and CMMPE differ for one stroke.

Figure 5 shows the distributions of the handwriting samples drawn with non-dominant hands per number of strokes. We applied a two-sided Wilcoxon signed rank test to verify the null hypothesis that the difference between the distribution obtained with MPE and the one obtained with CMMPE has zero median. The null hypothesis was rejected (*p-value* $= 1.85 * 10^{-07}$) and a right-tailed Wilcoxon signed rank test rejected the null hypothesis (*p-value* $= 9.31 * 10^{-08}$) in favour of the alternative hypothesis that the difference distribution has a median greater than 0, i.e. MPE extracts more strokes than CMMPE also in this case. Figure 6 shows that when the same sample is elaborated by the two algorithms the same number of strokes were extracted 130 out of 320 times (∼41%). For 110 out of 320 samples (∼34%) the motor programs extracted by MPE and CMMPE differ for one stroke.

Eventually, we compared the distributions of strokes extracted by MPE and CMMPE subject by subject. Each distribution was computed over all the samples drawn by each subject, therefore including the samples drawn by the two end-effectors. We performed 32 two-sided Wilcoxon signed rank test at the 5% significance level and for 12 subjects the null hypothesis that the difference between the distribution obtained with MPE and the one obtained with CMMPE had zero median was rejected.

4 Discussions

Table 1, Fig. 3 and Fig. 5 show that motor programs extracted from samples drawn with non-dominant hands are made up of a greater number of strokes with respect to the motor programs extracted by the sample drawn by dominant hands. Moreover, there is a greater variability in the number of strokes extracted from the samples written with the non-dominant effector. Even though motor equivalence suggests that samples generated by both the effectors are the executions of the same motor program, we postulate that the greater variability we observed in the motor program extracted by samples written with non-dominant hands is an effect of motor learning.

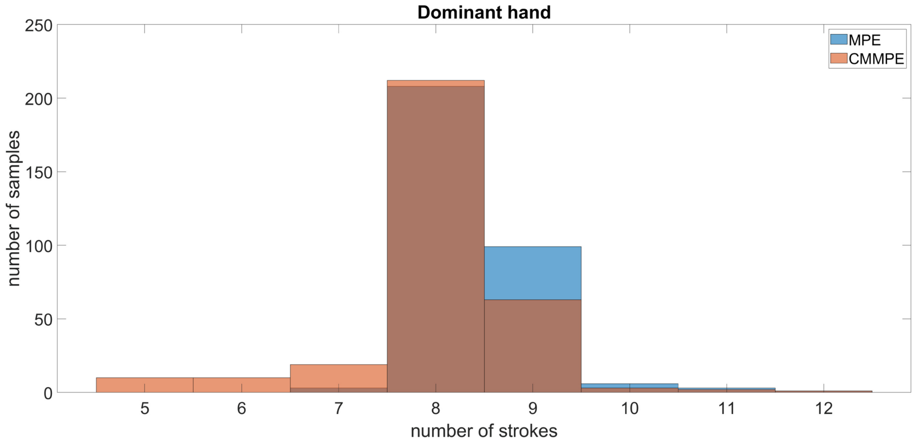

Fig. 3. Distribution of samples written with dominant hands per number of strokes.

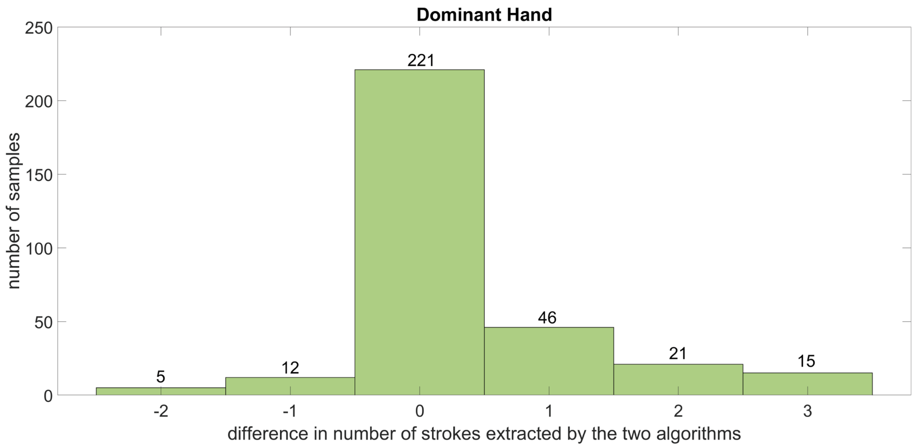

Fig. 4. Distribution of samples written with dominant hands per difference of strokes between MPE and CMMPE. The difference is computed with respect to the strokes extracted by CMMPE.

Subjects were not familiar with writing with their non-dominant effector and we hypothesize a motor learning process was triggered when they drew the desired trajectory with the new group of muscles. By limiting the maximum number of repetitions of the motor task with the non-dominant hand, we set the learning time equal to all the subjects even though different subjects may need a different time to learn a new motor task. In fact, it is known that the rate of motor learning is an individual feature and part of motor variability is an expression of the individual way each subject explores the motor command space [11]. It follows that, in the case of samples drawn by non-dominant hands,

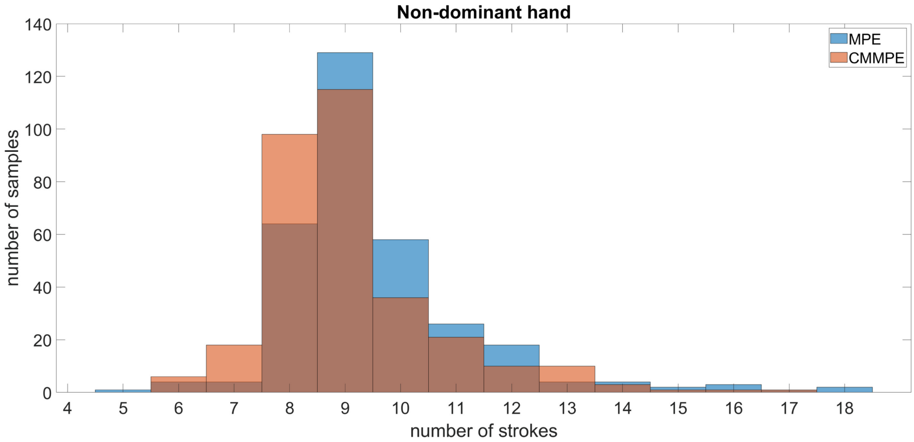

Fig. 5. Distribution of samples written with non-dominant hands per number of strokes.

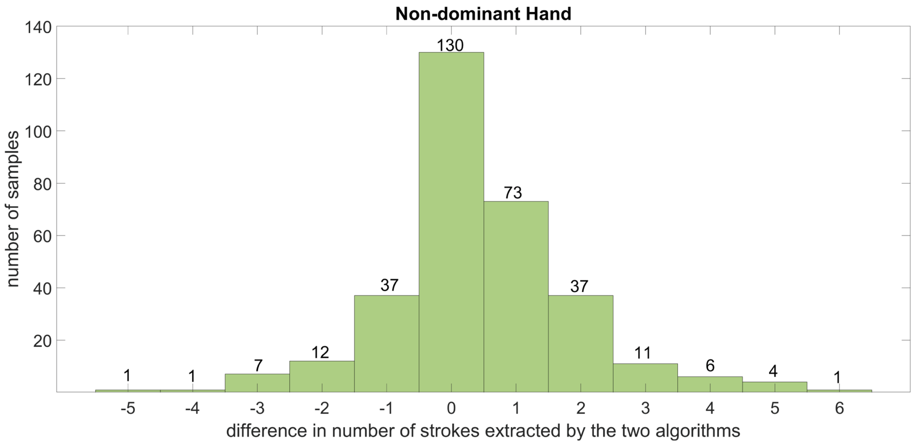

Fig. 6. Distribution of samples written with non-dominant hands per difference of strokes between MPE and CMMPE. The difference is computed with respect to the strokes extracted by CMMPE.

the correction of the ongoing movements was introduced only in part by the spinal cord but more significantly by supraspinal areas like the cerebellum, whose corrective actions differ from the ones executed by the spinal cord for latency, intensity and duration [1,26].

In order to take into account the individuality of learning and execution processes, both the algorithms were adjusted to each subject in a way that the variability in the number of strokes extracted from the samples drawn by the dominant hand was minimized. We analysed the selected parameters in order to verify if some values were more frequent than others.

For MPE, the most frequent couple of parameters, which was assigned to 14 out of 32 subjects, was ($V_{th} = 10\% * v_{peak}, T_{th} = 20\,\text{ms}$). The threshold $T_{th} = 20$ ms was selected for 30 out of 32 subjects while $T_{th} = 70\,\text{ms}$ and $T_{th} = 80\,\text{ms}$ were selected for the remaining 2 subjects. Values equal to or lower than $30\% * v_{peak}$ were assigned to V_{th} for 18 subjects. Overall, this analysis confirms that corrective movements are characterized by a short duration and a small amplitude for the majority of the subjects.

For CMMPE, the most frequent couple of parameters, which was assigned to 12 out of 32 subjects, was ($w = 3, \alpha = 0.6$). The parameter value $\alpha = 0.6$ was selected for 31 out of 32 subjects while $\alpha = 0.8$ was selected for the remaining subject. When $\alpha = 0.6$, a value equal to or lower than 4 was assigned to the parameter w for 22 subjects. Overall, this analysis suggests that the parameter α is roughly independent of the subject's motor skills.

Eventually, the statistical analysis presented in the previous section shows that CMMPE extracts fewer strokes than MPE, independently of the end-effector used to draw the samples. Nevertheless, the two algorithms extracted the same number of strokes from ~55% of samples (221 drawn with dominant hands and 130 with non-dominant ones) and they had a similar behaviour over the samples produced by 20 subjects. Overall, these results suggest that both the algorithms are modelling the same phenomena, i.e. the introduction of corrective movements to keep the ongoing movement close to the desired one, from a different perspective, and that CMMPE is more robust than MPE to noise or non-modelled motor variability that is an expression of the intervention of supraspinal centres.

These findings are in line with the results obtained by the algorithm IDeLog [8], which is used for the detection of the strokes that allow a high-fidelity reproduction of handwriting samples in terms of velocity and trajectory profiles. So, differently from MPE and CMMPE, it captures also small variations in velocity and trajectory because the aim is to perfectly reproduce a single sample rather than to find the general model behind many repetitions of the same movement. IDeLog was able to improve the reconstruction of a sample by analysing the velocity profile in search of target points and then exploiting the information about the curvature and the location of segmentation points in order to move the target points and improve the trajectory reconstruction.

5 Conclusions

We have proposed and compared two algorithms, MPE and CMMPE, that extract the motor program from the analysis of handwriting samples. Both the algorithms discriminate between movements that are embedded in the motor program stored in the brain and other movements that are generated in reaction to proprioceptive feedback. MPE discriminates between the two classes of movements by analysing the velocity profile of a sample and looking for peaks that correspond to corrective movements introduced by the spinal cord, while CMMPE detects the movements encoded in the motor program by observing the curvature profile with a multiscale approach.

By keeping in mind the experimental studies of Lashley and Raibert that led to the discovery of the motor equivalence phenomenon, we asked the participants to draw a trajectory with their dominant and non-dominant hands. Both the algorithms showed a greater variability in the number of extracted strokes when they analysed the samples written with non-dominant hands. This greater variability could be explained by taking into account that subjects were writing with their non-dominant hand for the first time and therefore our experiment triggered the cerebellar mechanisms devoted to learning a new motor skill. These considerations suggest organising data collection in different sessions so that in the last session the learning mechanism is off.

The experimental results have shown that both the approaches are able to extract the same number of strokes from different executions of the same drawing performed by a subject. Moreover, the number of strokes extracted by MPE is equal to the number of strokes extracted by CMMPE for $\sim$55% of the handwriting samples. CMMPE is resulted to be more robust to noise or non-modelled motor variability caused by the motor learning process triggered during the experimental session with non-dominant hands.

Our future investigations will be aimed at evaluating as the performance of each algorithm varies as the learning process progresses. We will set up a new data collection campaign organized in different sessions spanned over a longer period of time so that we will be able to capture the acquisition in the long term memory of the motor commands used to execute a motor plan with the non-dominant hand. Eventually, we plan to combine in a new algorithm the two approaches adopted by MPE and CMMPE so that the curvature will be analyzed to detect the position of the target points and the velocity will be analyzed to infer the parameters of the velocity profile of each elementary movement between two target points.

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