Uncovering Major Age-Related Handwriting Changes by Unsupervised Learning

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***Abstract*— Understanding how handwriting (HW) style evolves as people get older may be key for assessing the health status of elder people. It can help, for instance, distinguishing HW change due to a normal aging process from change triggered by the early manifestation of a neurodegenerative pathology. We present, in this paper, an approach, based on a 2-layer clustering scheme that allows uncovering the main styles of online HW acquired on a digitized tablet, with a special emphasis on *elder* HW styles. The 1st level separates HW *words* into writer-independent clusters according to raw spatial-dynamic HW information, such as slant, curvature, speed, acceleration and jerk. The 2nd level operates at the *writer* level by converting the set of words of each writer into a Bag of 1st Layer Clusters, that is augmented by a multidimensional description of his/her writing stability across words. This 2nd layer representation is input to another clustering algorithm that generates categories of writer styles along with their age distributions. We have carried out extensive experiments on a large public online HW database, augmented by HW samples acquired at Broca hospital in Paris from people mostly between 60 and 85 years old. Unlike previous works claiming that there is only one pattern of HW change with age, our study reveals basically three major HW styles associated with elder people, among which one is specific to elders while the two others are shared by other age groups.**

Keywords- Age Characterization; HW Styles; Unsupervised Learning; Two-Layer Clustering Scheme.

I. INTRODUCTION

Handwriting (HW) is a high-level skill, requiring fine motor control and specific neuromuscular coordination. It is well-known that handwriting evolves during lifetime and declines with age [1]-[3]. Handwriting also gets degraded when cognitive decline appears, or in case of illness [4][5]. Characterizing age from handwriting is thus important for two reasons: first, it may allow distinguishing a normal evolution of handwriting from a pathological one; second, it may allow inferring different possible patterns of HW evolution due to age, especially in healthy elders.

Several studies in the literature have tackled the problem of age characterization of healthy persons from both offline and online HW. Sometimes, this characterization is carried out by visual inspection [4]-[8] through observable features as for example letter size and width, slant, spacing, legibility or smoothness of execution, alignment of words w.r.t baseline, number of pen lifts, among others. On the other hand, sometimes it is carried out by extracting automatically features from the offline raw signal [9] or from the raw temporal functions of online handwriting acquired on a digitizer [1]-[3], [10]-[12].

All these works agree that age leads to a different behavior of the features extracted from handwriting: change in the distribution of velocity profiles [3], increase of in-air time [1] and of the number of pen lifts [5], lower writing speed [2][7][11], lower pen pressure [2][5][7], irregular writing rhythm, irregular shapes of characters and slope [5], and loss of smoothness in the trajectory [5].

In most of such works, it is implicitly assumed that there is a unique pattern of handwriting evolution with age. Their analysis is mostly based on descriptive statistics (analysis of variance, linear regression). Walton, nonetheless, noted by visual inspection on Parkinsonian patients and healthy controls that, according to writing rhythm, there are two major subpopulations of elders: half have a regular rhythm while half show an irregular one [5].

We propose in this work to infer automatically the main writing profiles, and to study their correlation with age. Our aim is to understand how HW evolves through age in terms of low-level information, namely kinematic and spatial parameters extracted from HW words, and in terms of high-level information, characterized by stability measures across words. Our approach is based on a 2-layer unsupervised clustering scheme that allows uncovering the main styles of online HW acquired on a digitized tablet, with a special emphasis on elder HW styles. The 1st level separates HW words into writer-independent clusters according to raw spatial-dynamic HW information, such as slant, curvature, speed, acceleration and jerk. The 2nd level operates at the writer level by converting the set of words of each writer into a Bag of 1st Layer Clusters, that is augmented by a multidimensional description of his/her writing stability across words. This 2nd layer representation is input to another clustering algorithm that generates categories of writer styles along with their age distributions. We have carried out extensive experiments on a large public online HW database, augmented by HW samples acquired at Broca hospital in Paris from people mostly between 60 and 85 years old, including several elders above 75, contrary to our previous works [13][14]. Thanks to this extended population, we go further than [13][14], as our study reveals extra patterns of handwriting evolution through age, contrary to the common assumption of a single pattern of evolution in previous state of the art. One of the main findings of our study it that there are, basically, three major HW styles that emerge as people age, among which one is specific to seniors and elders while the two others are shared by other age groups.

The paper is organized as follows. Section II presents the proposed approach including feature extraction, the two-level clustering scheme, and visualization techniques. Section III describes the experiments and gives qualitative and quantitative assessments of our HW-based age characterization. Finally, in Section IV, the main conclusions are drawn and future directions are pointed out.

II. PROPOSED APPROACH

In this section, we describe the feature extraction phase consisting of two stages, and we briefly describe the techniques we use to visualize HW features and the distribution of our multidimensional HW data.

A. *Feature Extraction*

Online HW acquisition provides 3 temporal sequences ($x(t)$, $y(t)$, $p(t)$) that correspond to the pen trajectory and pressure during the production of each word. At the 1st layer, 33 dynamic features are extracted: the horizontal and vertical speed computed at each point n as $V_x(n)=|\Delta x(n)/\Delta t(n)|$ and $V_y(n)=|\Delta y(n)/\Delta t(n)|$ where $\Delta x(n)=x(n+1)-x(n\text{-}1)$, $\Delta y(n)=y(n+1)-y(n\text{-}1)$ and $\Delta t(n)=t(n+1)-t(n\text{-}1)$, since the high temporal resolution (100 Hz) allows estimating the derivative at point n by considering its neighbors (n+1) and (n-1) as often done in the literature [15]. The V_x and V_y sequences are then converted each into a histogram of 4 bins determined through a quantification process. The same process is applied to extract horizontal and vertical acceleration and jerk histograms. Additionally, we include the pen-up duration ratio defined as in [1] by *PR* = (*Pen-up Duration*)/(*Total Duration*) and pen pressure and its variations quantized in 4 bins each. To extract the spatial static parameters, we first apply a resampling process, in order to ensure that all consecutive points in the word are equidistant, thereby making parameter values at each point equally representative, regardless of word dynamics. 21 spatial features are then extracted: the local direction θ and curvature φ computed at each point [15] and represented through histograms of 8 bins quantized in the range of 0º to 180º degrees, the number of pen-ups, the number of strokes (a stroke is defined as a writing movement between 2 local minima of speed along the y-axis), the average stroke length, and the length of the stroke projection on X and Y directions. Overall, we obtain 54 global descriptors characterizing the dynamics and spatial static shape of each word.

At the 2nd layer, a feature extraction process is carried out at the writer level to characterize people based on two kinds of information, raw spatiotemporal HW parameters, and intra writer word variability. First, using a Bag of Prototype Words (BPW) technique [16], we represent the HW samples by the clusters of words obtained at the first layer. This is done in order to generate the distribution of each writer's words over the first layer clusters, and therefore the HW style of persons in terms of the first layer parameters. Furthermore, we compute the Euclidean distance between each pair of words of a writer (distance between the first layer feature vectors) and quantize them into a 5-bin histogram. This histogram measures the variability of a writer across the set of words, and thus, the stability of his/her HW style. The dimension of second layer feature vector, obtained in this way, is equal to 5 + the number of clusters considered in the 1st layer.

B. *Two Layer Clustering Scheme*

HW style characterization is often approached using unsupervised techniques, such as clustering [17]-[19]. The reason to do so is that no *a priori* knowledge of the styles to characterize is available. These techniques, therefore, seek to cluster HW patterns that are similar, into groups that appear naturally in the population and define the latter as styles. However, these HW styles characterizations are often carried out at the level of characters, strokes and words [18][20][21], leaving aside the fact that writers may present some sort of variability in their styles across words. We consider this variability important to characterize HW styles. Therefore, we propose a 2-level approach: the 1st layer takes as input the dynamic and spatial parameters (low level information extracted from the raw signal), while the 2nd layer studies the HW style variability of the writers (high level information). At the first layer, we perform a clustering of the set of words (using the 54 features from Section II-A) regardless of the identity of the writer, generating word clusters that characterize low level styles. In the 2nd layer, the clustering is performed at the writer level, where each person is represented by his/her cluster frequency histogram and pairwise word distance histogram, in order to generate HW style categories that take into account the spatial and dynamic characteristics along with the writer's variability. We present the results carried out using K-means clustering on both layers (Hierarchical clustering was also tested, giving similar results). To automatically determine the number of HW categories (clusters), we used the Silhouette criterion [22] as we do not have any *a priori* knowledge on the actual number of HW styles.

C. *Visualization Techniques*

To visualize the quality of clustering, we use two dimensionality reduction techniques: Principal Component Analysis (*PCA*) and Stochastic Neighbor Embedding (*SNE*). *PCA* allows computing the correlations between features and the relevance of each for style characterization. *SNE* [23] is a non-linear method that projects the points from a high dimensional space onto a new space preserving distance relations between points as much as possible.

III. EXPERIMENTS

In this section, we describe our experiments including database description, the results obtained with the two clustering stages and the information theoretic measures we use to assess the effectiveness of our approach.

A. *Database Description*

For experiments, we use the IRONOFF database [24] of online HW word samples in English and French, acquired using a Wacom tablet (UltraPadA4) that records a sequence of tuples ($x(t)$, $y(t)$, $p(t)$) sampled at 100Hz with a resolution of 300 ppi. Although this database consists of 880 writers, only few are more than 60 years old (concretely 11 are between 60 and 77 years old). For a more reliable study of HW change as people age, we collected HW samples at Broca Hospital in Paris from a population of 25 persons with no diagnosed pathology, 23 of which have between 58 and 86 years old with an average of 72. These samples were also acquired on a Wacom Tablet (Intuos ProLarge) at the same sampling rate (100Hz) but at a higher resolution (5080 ppi); we thus decreased the resolution of the new samples to match the 300 ppi of the IRONOFF database. Combining both databases, we obtain 27,683 HW samples from 905 writers aged from 11 to 86 years old (Y.O.). For age characterization, we split the obtained database into 6 age groups as shown in TABLE I.

TABLE I. AGE GROUP DEFINITION

Category	Age Range	Num. of Writers
Teenagers (A1)	11-17 Y.O.	68
Young Adults (A2)	18-35 Y.O.	639
Mid Age Adults (A3)	36-50 Y.O.	133
Old Adults (A4)	51-65 Y.O.	43
Seniors (A5)	66-75 Y.O.	14
Elders (A6)	76-86 Y.O.	8

As seniors and elders are still underrepresented and age groups A2 and A3 are overrepresented, we balance, at the 2nd layer stage, the database in terms of age categories in order to ensure meaningful results: we divide the set of words written by a given person into groups from 10 to 15 words, and assign each resulting group to a virtual new writer, making sure that the generated writers do not share words. Finally, to properly evaluate the clustering and its correlation with age, we retain the same number of virtual writers for each age group. This number was set to 26 writers per age group (thus generating a total of 156 writers), which were selected through K-medoids clustering over each A_i in order to retain the most representative writers of each age group.

B. Quality of the Clustering (Entropy Efficiency)

In order to objectively analyze the effects of the clustering on age characterization, we introduce three entropy efficiency measures. The first one quantifies the predictability of a certain age group (A_i) distribution across the clusters, and is computed using (1).

$$\eta(A_i) = \sum_{k=1}^{N_C} \frac{p(C_k|A_i)\log_2(p(C_k|A_i))}{\log_2(N_C)} \qquad (1)$$

$$\eta(C_k) = \sum_{i=1}^{N_A} \frac{p(A_i|C_k)\log_2(p(A_i|C_k))}{\log_2(N_A)} \qquad (2)$$

$$E[\eta] = \sum_{k=1}^{N_C} \frac{|C_k|}{\left|\cup_{j=1}^{N_C} C_j\right|}\eta(C_k) \qquad (3)$$

The second quantifies the degree of disorder of a cluster w.r.t the distribution of the ages of the writers assigned to this cluster. It is computed using (2). Finally, the third one gives a general measure of the quality of the whole clustering as a sum of the entropy efficiencies of each cluster, weighted by the size of the clusters as shown in (3). All the entropy efficiency measures are normalized between zero (maximum order → perfect age predictability) and one (maximum disorder → no possible distinction of age groups). In (1), (2) and (3), C_i stands for the i^{th} cluster obtained in either the 1st or the 2nd layer; A_i corresponds to the i^{th} age group (defined in Section III-A); N_A is the number of age groups and N_C is the number of clusters. It is important to note that these measures are not used to select the optimal number of clusters (the Silhouette criterion [22] is used to this end), but to evaluate the quality of the clustering once it is carried out.

C. First Layer Clustering

Using the Silhouette method, we observe that 9 is the optimal number of clusters for the 1st layer. Figure 1 shows the 9 word clusters obtained by the K-means algorithm run over all the HW word samples, projected on the PCA plan spanned by the first two eigenvectors. As these two axes represent only 37% of the variance, some clusters overlap. Figure 2 shows samples of words in each cluster, when characterized by speed, acceleration and jerk. Through PCA analysis, we can attribute to each cluster particular characteristics w.r.t the dynamic and spatial features. These characteristics are described in TABLE II and TABLE III below:

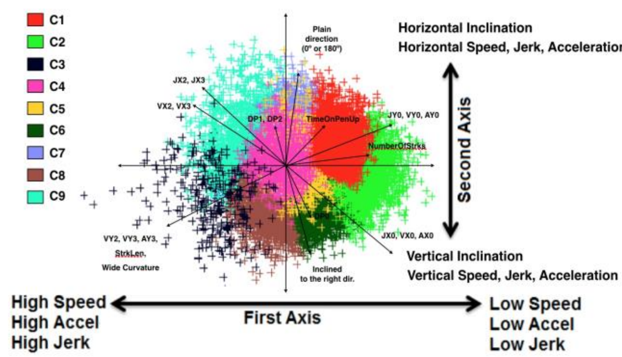

Figure 1. PCA Projections of First Layer Clustering

TABLE II. DYNAMICS IN FIRST LAYER CLUSTERS

	Dynamic Features
Cluster 1	Low Speed/Accel/Jerk
Cluster 2	Low Speed/Accel/Jerk
Cluster 3	High Speed/Accel/Jerk
Cluster 4	Average Speed/Accel/Jerk
Cluster 5	Average Speed/Accel/Jerk
Cluster 6	Average Speed/Accel/Jerk on Y; low on X
Cluster 7	Average Speed/Accel/Jerk
Cluster 8	High Speed/Accel/Jerk on Y; average on X
Cluster 9	Very high Speed/Accel/Jerk

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Figure 2. HW Samples in each Cluster of the 1st Layer with a color scale quantifying the magnitude of speed (left column), Jerk (center), and acceleration(right)

TABLE III. OTHER FEATURES 1ST LAYER CLUSTERS

	Pressure	**Inclination**	**Curvature**
Cluster 1	Average	Straight	Round
Cluster 2	Low	Straight	Round
Cluster 3	Average	Inclined to right	Straight
Cluster 4	High	Inclined to right	Straight
Cluster 5	Average	Straight	Average
Cluster 6	Average	Straight	Average
Cluster 7	Average	Straight	Round
Cluster 8	Average	Straight	Straight
Cluster 9	Average	Inclined to right	Straight

D. Second Layer Clustering

At the second layer, the Silhouette method reveals 8 optimal categories. Figure 3 shows the SNE projections of the 8 categories obtained by *K*-means run on the set of writers' 2nd layer descriptors, and Figure 5 shows some HW words of the most typical writer in each category (usually the writer whose representation is closest to the category center), when characterized by speed. In this layer, each point represents a writer, described by 14 features:

- 9 features for the histogram of distribution of his/her words over the 1st layer clusters.
- 5 features for his/her histogram of intra-writer word pairwise distances.

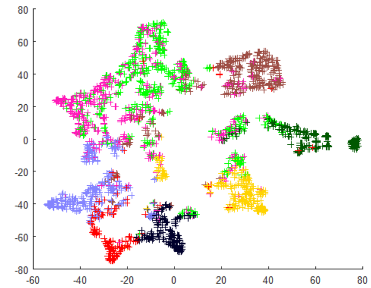

Figure 3. SNE Projections of the 2nd Layer Categories

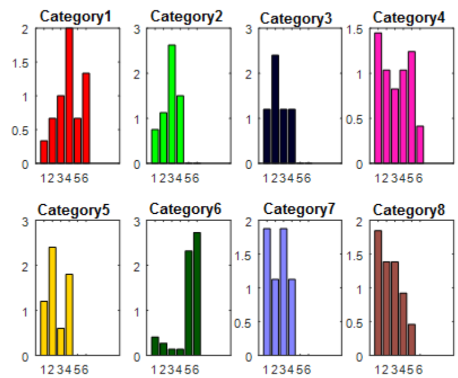

Figure 4. Age distribution in each Category of the 2nd layer

TABLE IV. 2nd LAYER CATEGORIES SIZE W.R.T BALANCED DATABASE SHOWING THE PERCENTAGES OF SENIORS (A5) AND ELDERS (A6) CONTAINED

	Cat 1	Cat 2	Cat 3	Cat 4	Cat 5	Cat 6	Cat 7	Cat 8
Size	18	16	10	29	10	44	16	13
Seniors	11%	0%	0%	21%	0%	39%	0%	8%
Elders	22%	0%	0%	7%	0%	45%	0%	0%

As we can see in Figure 4, Category 6 gathers mostly persons above 65 years old (this can be seen also in TABLE IV). This Category is the most stable, as writers maintain a relatively constant HW style across words. This Category is also represented by Cluster 2 in the 1st layer (as we can see in Figure 6) characterized by the lowest velocity, acceleration and jerk, as well as very round HW with the highest number of strokes and smallest stroke length (as shown in the first layer's cluster characterization). Therefore, as Category 6 contains the highest number of persons (44 writers), this could indicate that the most common evolution pattern of aged persons is to develop a slow and curved HW with a medium to high "time on pen-up" (time in air) probably produced by hesitations when writing.

We also observe that Category 1 contains a considerable quantity of persons aged above 75 years, as well as middle-aged individuals. This Category is the one with the highest instability and is highly correlated to cluster 9 in the 1st layer, which is characterized by the highest velocity, acceleration and jerk along with a low number of larger strokes. This could indicate the existence of a group of aged people that share with middle-aged people a more agile and fast HW, with tendency to produce long and straight strokes and a large style variation across words.

Category 7 is also interesting since its age distribution contains all the age groups except the persons above 65 years old. This category is correlated to cluster 8 in the 1st layer clustering stage. This group of people is characterized by high velocity, acceleration and jerk in the vertical direction but an average value of these parameters in the horizontal axis, as well as high pressure during writing. Thus, this could indicate that other features that separate teenagers and middle-aged adults from the persons above 65 years are a fast vertical HW with high *y*-axis velocities and jerk due to the upper and lower loops that represent high vertical stroke variance, but with an average velocity and jerk in the x-axis. Therefore, an average jerk and velocity in the horizontal axis could be an evidence of careful writing characterized by less variable strokes as the person writes in the horizontal sense, but at the same time, with high vertical velocity and acceleration to rapidly make the upper and lower loops.

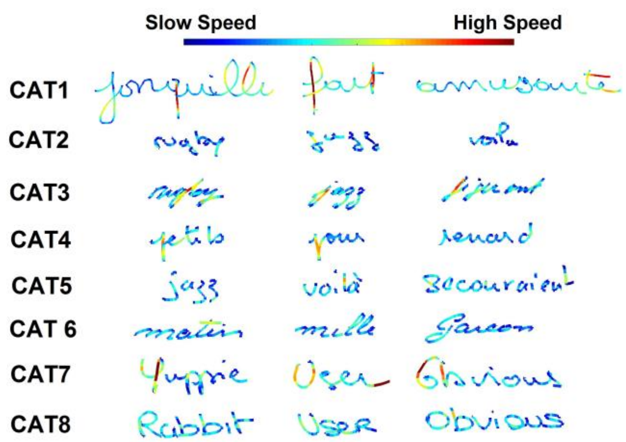

Figure 5. HW Samples from each Category of the 2nd Layer showing Speed on a color scale

We also notice that the 3rd category in the 2nd layer, which has average instability, also contains all the age groups but the persons above 65 years. This category is correlated to Cluster 4 in the 1st layer, with the highest pressure and low jerk on the *x*-axis, as well as a lot of sharp HW turns. This could be an indicator, as we saw above in the analysis of Category 7, that a low jerk on the horizontal direction and a relatively high HW pressure could separate the old people from the rest of the population.

Category 2 is another one that contains only persons from age groups A1 to A4, thus revealing other features that separate the elder persons from the teenagers and middle-aged groups. This category is related to Cluster 1 and 6 in the 1st layer. Cluster 1 is characterized by low velocity and acceleration with average number of small strokes, average pressure and average pressure variation. Cluster 6 consists of average velocities and accelerations as well as of an average number of pen-ups with short duration and an average number of strokes with average size. Both clusters share a very low horizontal jerk (that proved to be an important feature to separate elders from the rest of the population), an average pressure and an average pressure variation.

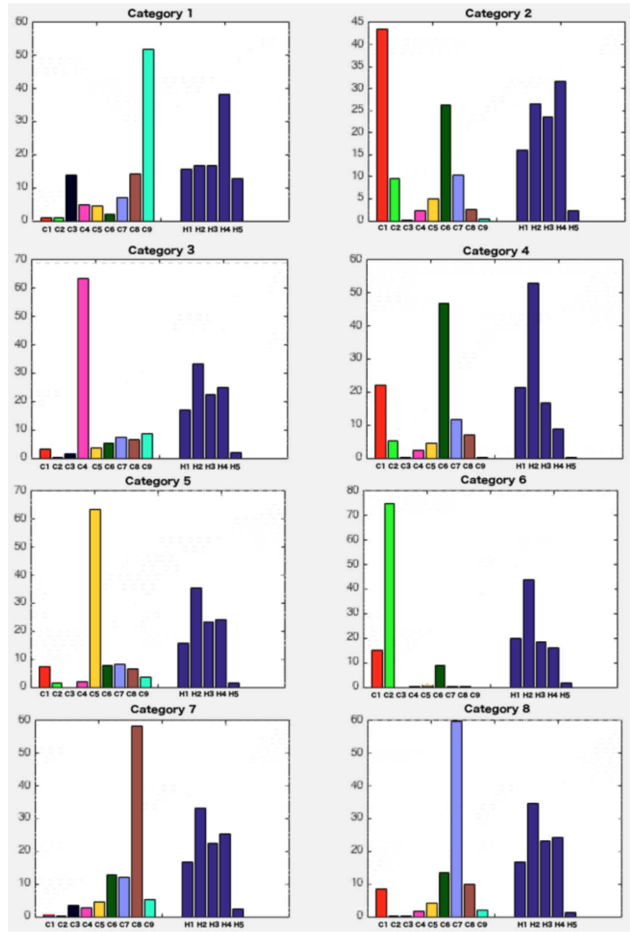

Figure 6. Representation of the 2nd layer categories w.r.t. the 1st layer clusters and the histogram of distances between words

Categories 4 and 8 are meaningful since they unveil differences between the eldest (A6) and the rest of the population. Category 4 consists of features that separate all the groups (A1-A5) from the eldest. On the other hand, Category 8 contains fewer elders. Such an age distribution could indicate that the HW style consisting of average velocity, acceleration and vertical jerk and low horizontal jerk is less frequent as age increases, thus characterizing the HW aging evolution. In other words, Category 8 uncovers a typical, albeit non-frequent, HW style of elders that consists of a low horizontal jerk even though speed, acceleration and vertical jerk have average values. Categories 4 and 8 have very high and medium stability, and they are also correlated to Clusters 6 and 7 in the 1st layer, respectively. This means that both categories have relatively low jerk in *x* w.r.t velocity and acceleration, which is also the case for categories 2, 3 and 7 that do not contain none of the two elder groups (A5-A6). We also notice that category 4 has very low pressure variation and lower jerk on *x* than in category 8 (which also has high pressure variation); thus, these elements could explain a very high stability for category 4 but no for category 8.

Overall, we see that three different types of aged persons emerge based on their HW styles and stability:

- Category 6: This is the most frequent in elders and seniors (71.2%) and is associated with slow velocity and acceleration and a stable HW style, high time on air and a large number of pen-ups. These characteristics are indicative of a slower and less fluent HW.
- Category 1: It represents 11.5% of old people and it consists of a HW style closer to that of middle-aged persons in terms of dynamic features. People in this group show the highest velocity, acceleration and jerk, as well as a very high instability across words, which is the opposite behavior to Category 6.
- Category 4: This is a new category of aged population emerging w.r.t our previous works [13][14]. It represents 15.4% of old writers and is characterized by a HW with average velocity, very low horizontal jerk, average pressure, low pressure variation and high instability across words.

E. Entropy Efficiency Measures

We measure the global entropy efficiency of the clustering as defined in (3) in terms of age distribution, on the balanced dataset with the same number of writers in the 6 age groups as described in Section III-A. The reduction of entropy measures how efficient is the clustering across layers in detecting HW styles that describe age tendencies. The result is shown on TABLE V, where we can observe how the 2-layer approach reduces the entropy at each layer, which means that our clustering detects HW styles with different age distributions. Also, a lower entropy efficiency in Layer 2 than in Layer 1 demonstrates that the stability of each writer HW style across words gives additional information for characterizing HW evolution though age.

TABLE V. TOTAL ENTROPY EFFICIENCY ACROSS LAYERS

	Layer 1	Layer 2
Entropy Efficiency $E[\eta]$	0.8365	0.7935

TABLE VI shows the entropy efficiency inside each of the Categories of the 2nd layer as computed by (2). The lower the entropy efficiency, the more predictive is the category of the writer's age. We observe that Category 6 (mostly composed by elders) shows the lowest entropy, followed by Categories 2, 3, 5 and 7, where no elders appear. This shows that these are the most interesting categories to analyze, in search for parameters which allow us to classify the elder population. In particular, one of the main findings is the HW style uncovered by category 6 which is the one that best predicts if the writer is an elder person. Likewise, the HW styles uncovered by Categories 2, 3, 5 and 7 have good age prediction capabilities and in particular they rule out that the writer is an elder person.

TABLE VI. ENTROPY EFFICIENCY AT EACH CATEGORY

	Cat 1	Cat 2	Cat 3	Cat 4	Cat 5	Cat 6	Cat 7	Cat 8
$\eta(C_K)$	0.92	0.72	0.74	0.97	0.71	0.68	0.76	0.85

Finally, we also compute, using (1), the entropy of each Age group w.r.t the clusters on both layers. This allows us to detect which age groups introduce an entropy reduction for the clustering. The lower the entropy, the more predictable the age group of the clusters it will fall into, i.e. the HW style or styles it will produce. The results of the cluster entropy efficiencies are shown in TABLE VII. We observe that the only age groups which introduce significant entropy reduction are A5 and A6, composed of people above 65 years old.

TABLE VII. ENTROPY EFFICIENCY AT EACH AGE GROUP

	A1	A2	A3	A4	A5	A6
$\eta(A_K)$ Layer1	0.91	0.96	0.96	0.96	0.56	0.42
$\eta(A_K)$ Layer2	0.92	0.98	0.92	0.94	0.45	0.33

This entropy reduction proves our approach's capacity to characterize the HW of the elder population through few categories of writers, and to discover a limited set of different evolution patterns that the HW style exhibits as people grow old. On the other hand, observing almost no entropy reduction for age groups A1 to A4 implies that the HW style for these age groups shows a great variability across the population. Each person from 11 to 65 Y.O. can develop any HW pattern with a similar likelihood; in other words, there is no clear way to separate these age groups.

IV. Conclusions and Perspectives

Our study has uncovered three different types of aged persons according to their HW styles and stability:

- The most important writing pattern in elders and seniors (Category 6) is associated with slow dynamics and a stable HW style, consisting of high time on air and a large number of pen-ups, probably due to hesitations between strokes. This group, which is the most represented among the aged population (71.2%), has the highest number of strokes. Overall, these characteristics are indicative of a slower and less fluent HW.
- Some old people (11.5%) represented by Category 1, have a HW style closer to that of a subset of middle-aged persons in terms of dynamic features. People in this group show the highest velocity, acceleration and jerk, as well as a very high instability across words, which is the opposite behavior to the previously described writing pattern of Category 6. They also present few and long strokes, which indicates a high fluency when writing. It is worth noticing that this writing pattern is overrepresented among elders (A6) w.r.t seniors (A5). Indeed, there are some very aged persons that maintain handwriting skills.
- Finally, a new category of elders emerges comparatively to our previous works [13][14]: These are the old writers (A5 and A6) represented by Category 4, which are distinguished from a large part of the rest of population by a HW with average velocity, very low horizontal jerk, average pressure, low pressure variation and high instability across words. It seems to be an intermediate

writing pattern compared to the two previous ones, and appears to represent 15.4% of the population.

- There are about 28.8% of elders and seniors whose HW style cannot be distinguished from the average adult population. These aged writers are persons who maintained their skills as they aged, writing in a similar way than some parts of the adult population. From this skilled aged population, 60 % are senior writers (A5) and 40% are elder writers (A6). This corroborates the tendency that the older a person gets, the more likely he/she will lose HW skills and fall into the group represented by Category 6.

Another interesting finding by our approach is the fact that categories 2, 3, 5 and 7 do not contain any old persons (A5 or A6). These categories disclose different HW styles of all the population except elders (A6) and seniors (A5). Categories 2 and 3 have average and low velocities and low and high stability, respectively, but they share a very-low horizontal jerk w.r.t speed and acceleration that is not present in old population HW (the latter often features low jerk but this is explained by the fact that speed and acceleration are also low). Category 3 also has the highest pressure and low pressure variation, which seems to be other discriminative features between old people and the rest of the writers. Category 7 has average horizontal velocity, acceleration and jerk and high vertical velocity, acceleration and jerk, and a low number of long strokes (high fluency) and high pressure. This HW fluency is another useful feature that discriminates part of the elders from the rest of the population. These results confirm our previous findings in [13][14].

Following this study, we are currently collecting a dataset of HW samples at Hospital Broca in Paris from elder people with Alzheimer and MCI cognitive disorders. Adding this population to the control population that served in this work, we will generalize our approach in order to assess its efficiency in automatically detecting HW styles associated with Alzheimer, MCI and Control persons.

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