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RESEARCH ARTICLE

Handwriting Assessment Using a Haptic Joystick for Rehabilitation Purposes

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ABSTRACT Writing skills play a major part in communication, whether in a typing or in a handwriting scenario. Thus, a decrease or even loss of these skills can be a major setback. The system described herein aims to promote handwriting rehabilitation through haptic guidance and analysis of characters written using a haptic joystick. The first goal of this work is the creation of a system that encourages a user to write better through repetition, and thus have an impact on the proprioceptive system. In the second part of this work, there is a character analysis model evolution. Character analysis is performed by digit or letter classification and quantification of written characters quality. As such, different methods are studied and evaluated to achieve the best classification accuracy. Regarding handwritten characters classification, the pre-eminent procedure for digits consists in the use of Histogram of Oriented Gradients coupled with a multiclass Support Vector Machine (HOG-SVM) whereas for letters the strategy involves using a Convolutional Neural Network (CNN). For handwriting quality quantification, Dynamic Time Warping (DTW) was performed between the written character and a reference image of the same character. Finally, haptic guidance impact in a handwriting retraining in rehabilitation scenario is evaluated.

INDEX TERMS CNN, DTW, handwriting rehabilitation, haptic joystick, HOG-SVM.

I. INTRODUCTION

Nowadays, writing is still one of the most important skills to possess, alongside speaking, listening, and reading. Whether in a digital or a traditional way, the ability to write allows the development of thinking skills, the expression of opinions, or even to serve as a proof of identity [1]. Consequently, losing the ability to write is a major drawback that requires tackling as soon as possible. The process of creating text with a writing instrument requires a panoply of underlying skills, including complex motor and cognitive skills, like for example fine motor control, in-hand manipulation, visual perception, visual-motor integration, and others [2].

In terms of background, the study of the hand is a widely sought-after field of research, mainly because most of daily activities rely on this body part. The complexity of the hand and its vast number of medical conditions make hand rehabilitation a field of study with plenty of developed work.

Due to the high and well-known stroke prevalence [3], a lot of the applications that are developed to promote hand rehabilitation mention and target individuals who suffered complications due to this disease. There are tablet applications [4], [5] for this kind of rehabilitation, interactive games that include letter tracing [6], mechanical products (such as Neuroball by Neurofenix [7], pneumatic devices [8], [9], exoskeletons [10]), or others making use of Virtual Reality [11].

Handwriting is a personal way of graphic communication and constitutes from 31 to 60% of children school days [2]. As such, mastering handwriting is a long process and important for academic success. This task is of vital importance not only for children, but is also required in the adulthood,

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as it enables a form of identification through signatures, an essential step in authorizing documents or writing cheques.

Dysgraphia is a disorder that affects writing skills of 5 to 20 percent of all children [12].

In adults, stroke is the second largest cause of death and the number one source of long-term severe adult disability worldwide [13]. A large proportion of strokes interferes with middle cerebral artery blood supply, consequently interfering with the motor cortex, which is responsible, among other activities, for handwriting. Given the human and economic burden of stroke, post-stroke care is of extreme importance.

The developed system aims to promote handwriting rehabilitation through movement repetition and handwriting analysis of people that have learning disabilities, such as dysgraphia, or limitation of fine motor skills (e.g., post-stroke) and could also be applied in other cases.

A haptic joystick was chosen for this purpose since it can provide live feedback by applying force to the user's hand, thus aiding in the process of handwriting training and, at the same time, performing hand rehabilitation through movement repetition of drawing letters and digits.

The first step of this work, developed in a previous M.Sc. dissertation [26], consisted in the creation of a haptic handwriting system that enabled the use of the haptic joystick as a writing guiding tool. The features of the first iteration of the system make the joystick useful for training, while the goal of the second part of this work is the assessment of writing skills. The combination of both gives the user the option to train or evaluate the writing skills.

Handwriting assessment consists in digit or letter classification, making use of the National Institute of Standards and Technology Special Database 19 [14], and quantification of characters quality. The general framework of this work can be seen in a flowchart form in the next section. Assessing the ability to perform recognizable writing is important for the hand rehabilitation evaluation progress. For the classification part, i.e., the identification of the written character, the methods evaluated were Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients coupled with a multiclass Support Vector Machine (HOG-SVM).

For the quality quantification part, the method assessed was Dynamic Time Warping (DTW). The use of DTW in the handwriting evaluation was validated by Carlo et al. [27], that states that DTW was considered to be a significant improvement on earlier computerized methods for evaluation of characters shape and legibility of the handwriting.

In short, the first step, useful for training, comprises the creation of an application that enables both user-joystick interaction and user guidance through lowercase vowels and geometric shapes. The second part of this work, made for evaluation, does not include haptic guidance, and consists in the identification of what the user wrote or quality assessment of the written character.

From a clinical point of view, retraining through obtaining consecutive good results during a rehabilitation process can be beneficial in improving motor and cognitive abilities, thus having an impact on the proprioceptive system [29]. The most relevant innovation of this work is to tackle this problem using a robotic approach, implementing and validating the automatic haptic guidance in the process of handwriting retraining in rehabilitation.

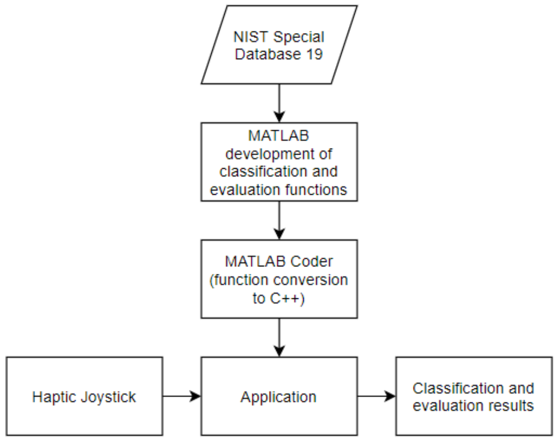

FIGURE 1. **Flowchart of the underlying procedure of handwriting analysis implementation.**

This way, the system described herein could be a complement in post-stroke therapy, enabling handwriting training through repetition and could also intervene in school dysgraphia diagnostics as a handwriting performance tool.

The materials and methods used and assessed in this work are present in Section II. This assessment and method iteration are present in Section III. In Section IV, the results are shown and discussed. The conclusions and future work proposals are present in Section V.

II. MATERIALS AND METHODS

In order to have a system capable of performing both handwriting training and analysis, several materials and methods were used. The framework of this work can be seen in a form of flowchart in Fig. 1.

The implementation of the system's haptic functions in the form of an application was made using OpenHaptics toolkit and its library Haptic Device API (HDAPI), which provides low-level functions for interaction with the haptic device. Qt Vs Tools, a Visual Studio extension, was also used to implement Qt functionalities (a multiplatform framework that enables graphical interface development).

The MATLAB functions mentioned in Fig. 1 made use of different methods. The choice of the methods to evaluate was based on the most used methods found in the literature. To build a character analysis model, an experimental study was performed, where the methods were evaluated in the classification of collected real handwriting.

Concerning materials, the herein reported experiments were performed on an Intel(R) Core (TM) i3-4010U CPU @ 1.70GHz, with 4 GB of RAM and a NVIDIA GeForce 820M GPU. A haptic joystick was used as a writing tool. The dataset used to apply the methods (described in more detail in a

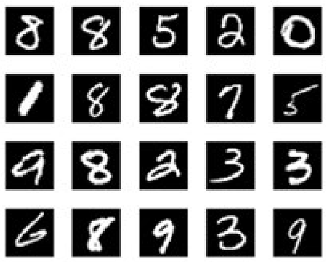

FIGURE 2. MNIST dataset example images.

FIGURE 3. EMNIST dataset examples images: EMNIST Digits (left) and EMNIST Letters (right).

subsequent section of this chapter) was the National Institute of Standards and Technology (NIST) Special Database 19 [14] and its variations (MNIST [15] and EMNIST [16]), which contain over 800,000 character images. The images have a size of 28 by 28 pixels.

MNIST dataset, with example images shown in Fig. 2, is split into training and testing sets, which contain 60,000 and 10,000 images of digits, respectively. This dataset does not contain an equal number of samples per class, i.e., contains a different number of images for each digit.

EMNIST dataset contains six different subsets. The ones that were used in this work were EMNIST Digits and EMNIST Letters, both of which have an equal number of samples per class.

EMNIST Digits is composed of 280,000 characters (24,000 in the training set and 4,000 in the testing set for each digit), and EMNIST Letters has 145,600 characters (4,800 make for the training set and 800 the testing set for each letter). Example images of both datasets can be seen in Fig. 3. EMNIST Letters contains 26 different classes, one for each letter, as uppercase and lowercase versions of the same letter make for a single class.

For handwriting acquisition and novel haptic handwriting training, the haptic joystick Touch by 3D Systems, shown in Fig. 4, was used.

A writing platform [17] was used to give the joystick a more user-friendly experience, as it better mimicked traditional writing (see Fig. 5). The use of this platform positions the base of the joystick 52 mm below the platform, allowing the tip of the joystick pen to touch the writing plane.

The methods used in this work to perform character classification and quantification of written characters quality made use of Machine and Deep Learning:

- Convolutional Neural Network (CNN)

FIGURE 4. Haptic joystick Touch by 3D Systems.

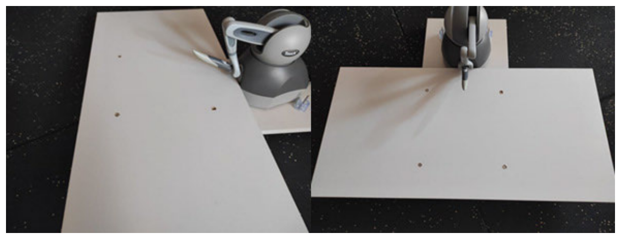

FIGURE 5. Writing platform used in conjunction with the haptic joystick.

- Histogram of Oriented Gradients (HOG)
- Support Vector Machine (SVM)
- Dynamic Time Warping (DTW)

A Convolutional Neural Network (CNN) is a subclass of neural networks [18] that contains one or more layers of convolution units. Histogram of Oriented Gradients (HOG) is a feature descriptor used to extract features from image data. Support Vector Machine (SVM) is a Machine Learning algorithm, used to analyze data for classification and regression analysis. This method is used herein as a non-binary linear classifier to classify HOG features [19]. DTW is a method to optimally align, i.e., to minimize the sum of distances between respective points, of two given signals [20]. In this work, DTW is performed between images instead of signals, so that the sum of distances between respective pixels is minimal. As such, the comparison between two images using this algorithm returns a sum of distances, evaluated herein to perform handwriting analysis.

Automatic written character classification was developed using MATLAB R2019b. The application that implements the joystick haptic functions performs linkage between the haptic device and the implemented functionalities.

As the interface was written in C++, MATLAB Coder application was used to convert from one programming language to the other. This way, it became possible to include the developed methods in the interface, making use of Visual Studio 2017, Qt 5.14.2, and Qt Visual Studio Tools 2.7.1.

To be able to generate and run the converted CNN code in C++, Intel Math Kernel Library for Deep Neural Networks (Intel MKL-DNN) was built and used, according to MathWorks build instructions [21].

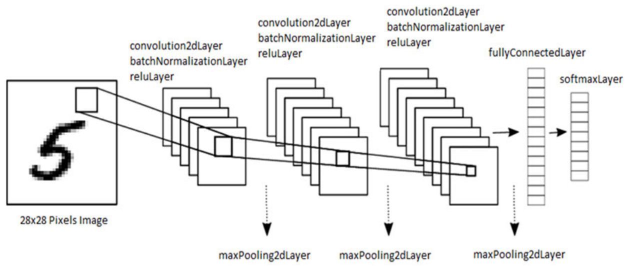

FIGURE 6. Convolutional neural network architecture used. Image adapted from [23].

For character quality quantification, MATLAB R2021b was used since this version supported code generation to C++ for the used methods.

CNN described in this work were trained using MATLAB, making use of the Deep Learning Toolbox. The general architecture and the procedures were the same as those found in a MathWorks example [22].

As shown in Fig. 6. the layers of the CNN consist of three consecutive sets composed of a 2-D convolutional layer, a batch normalization layer, and a rectified linear unit layer, followed by a max pooling layer.

The convolutional layers have, from left to right, 8, 16 and 32 filters of size $[3 \times 3]$. All three of the convolutional layers have "SAME" padding (layer output the same size as the layer input size). The max pooling layers have pooling regions of $[2 \times 2]$ and a stride of $[2 \times 2]$.

The images used in the example are subdivided in ten folders, each containing 1000 examples of the same digit, thus making a total of 10000 images. They can be found inside MATLAB root folder and are made available upon installation of the Deep Learning Toolbox. The images are 28 by 28 pixels.

As there are no originally defined validation/test images, the authors of the example split the 1000 images in two sets: one containing 750 for training and the other with 250 for validation/testing.

Images used for validation serve to periodically evaluate the network performance during training and are not used for training nor to update the network weights. Images used for testing purposes are availed at the end of the training process to do accuracy assessments. In the MathWorks example, the images split from the training set are used for both validation and testing, hence the validation/testing designation.

One other used method was composed of HOG coupled with a SVM, which was also based on a MathWorks example [24]. In the example, HOG feature extraction was performed using cells of 4 by 4 pixels. The features, based on the directional changes of color along the image, are then used to train the multiclass classifier (SVM).

III. DEVELOPED WORK

The first step of this work was the creation of a haptic handwriting system in which the user can choose between three types of exercises and two orientation modes. The different exercises consist in drawing geometric shapes and writing vowels and signatures. The two orientation modes are the guided mode, which guides the user's hand through a reference letter writing path, point by point, and the semi-guided mode that only applies corrective forces if the individual deviates from the reference path. Using the guided mode, it is possible to change in the software the dimension and execution time of the trajectory, while using the semi-guided mode it is only possible to adjust the dimension of the trajectory because the execution time is controlled by the user. The system allows character classification with intelligent techniques and the evaluation of the quality of the handwriting using the DTW.

A. HAPTIC IMPLEMENTATION

The position of the device is obtained through sensors located on the axis of the device and then stored in matrices, while the reference path is stored in comma-separated values files, which are read, and the paths are then copied to matrices. The calculation of the force to be sent to the haptic device is performed using a proportional controller with a gain of 0.9. This value was obtained by trial and error, and 0.9 was the gain value for which the haptic device offered a more user-friendly experience. The reference trajectory and the actual trajectory are visualized through the graphical interface that provides visual feedback and allows the evaluation of the user's progress.

B. CHARACTER CLASSIFICATION

After having the haptic functions implemented, the next step consisted in the development of handwriting analysis by classification and evaluation.

The first networks were trained for digit classification, due to having a smaller number of possible outputs when compared to letter classification, thus making the process simpler. Three CNN were trained, making use of the Deep Learning Toolbox dataset mentioned in the previous chapter: the complement of those images, the binarized version and with data augmentation. The validation/test accuracy values were on par with literature values, the lowest one being 98.93%.

To analyze the performance of the CNN in classifying handwriting, eight subjects (four males, four females, ages 14, 28, 29, 44, 52, 56, 74 and 80, seven of which right-handed and one left-handed) were asked to write the numbers from zero to nine in a white blank sheet of paper (an example can be seen in Fig. 7). The sheet of paper was then scanned in grayscale and the digits were cropped, giving a total of 80 images, and resized into 28 by 28 pixels so that they could be classified by the CNN.

While the CNN seem to successfully classify the dataset images, the same did not occur in a real handwriting scenario, since the classification accuracy values decreased in more than 30% for every CNN.

Another CNN was trained using MNIST dataset, with the same network architecture and training options as the

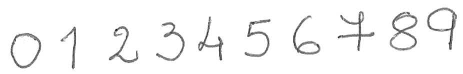

FIGURE 7. Handwritten digits sample.

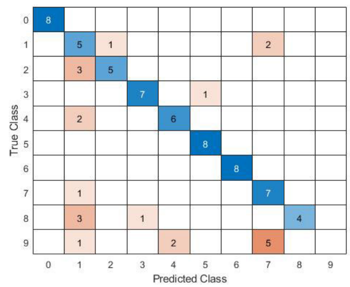

FIGURE 8. Confusion chart for handwritten digits classification using a CNN trained with MNIST dataset.

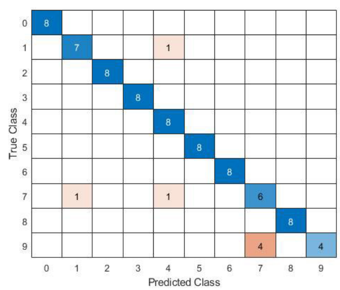

FIGURE 9. Confusion chart for handwritten digit classification with Histogram of Oriented Gradients coupled with Support Vector Machine (HOG-SVM), using MNIST dataset.

previous ones, to evaluate if the low accuracies obtained were due to the fact that the dataset used was computer generated. MNIST was created using real handwriting and therefore is not a synthetic set.

Analogously, the resulting CNN was used to classify the same images. The accuracy of this classification was 72.50% (respective confusion chart in Fig. 8), and although it was higher than the previous ones, it was still very low when compared to validation/test accuracy values.

As the CNN achieved lower classification accuracy than expected, another method was evaluated.

The method consists in the use of Histogram of Oriented Gradients coupled with a Support Vector Machine (HOG-SVM), as described in a MathWorks example [25]. To employ this method, MNIST dataset was used. The results were far better than the previous two, and 91.25% accuracy was achieved (respective confusion chart in Fig. 9).

Regarding letter classification, there was a similar strategic approach. The same eight subjects that were asked to write the numbers were asked to write the modern English alphabet, both in uppercase and lowercase (see example in Fig. 10). The letters were individually cropped, leading to 52 images for each subject, giving a total of 416.

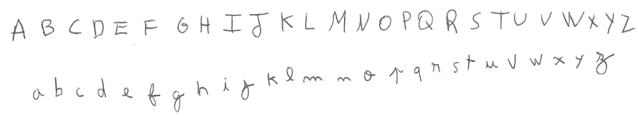

FIGURE 10. Handwritten letters sample.

TABLE 1. Handwritten digits classification accuracy comparison between MNIST and EMNIST Digits with the use of different methods.

	CNN	HOG-SVM
MNIST	72.50%	91.25%
EMNIST Digits	92.50%	97.50%

Firstly, a CNN was used to classify the 416 images. From this point onward, only the binarized form of the images was classified since the acquisition mode by the joystick application is made in ones and zeros. The CNN was trained with EMNIST Letters dataset, and the classification had an accuracy of 75.72%.

The next step involved employing HOG-SVM method to classify the same letter images, using the same dataset as the CNN. HOG-SVM achieved an accuracy of 73.32%. The low accuracy obtained can be due to the existence of more possible output classes when compared to digit classification. Furthermore, the presence of both uppercase and lowercase letters in the dataset increases intraclass variation and could thus decrease SVM classification accuracy.

Considering every previous character classification accuracy, MNIST seems to be underperforming when compared to EMNIST Letters. Notwithstanding the fact that one dataset contains digit images and the other letters, EMNIST Letters achieved better accuracies with more than double the possible output classes. The two main differences between the datasets are the number of images and equality or not of the number of samples per class. To verify if a dataset with more images and equal number of samples per class would perform better, tests using a CNN or HOG-SVM that were made with MNIST were performed with EMNIST Digits.

The results were as follows: classification with only a CNN had an accuracy of 92.50%, with HOG-SVM an accuracy of 97.50%. Even though the CNN and HOG-SVM using MNIST were trained with grayscale images and using EMNIST Digits with binarized images, EMNIST Digits proved to be superior, whether because of the balanced number of images per class or due to the substantially larger number of images.

Taking into consideration Table 1 results, EMNIST Digits was the chosen dataset to perform digit classification, replacing for this matter MNIST dataset.

Both EMNIST Digits and EMNIST Letters were chosen for performing handwritten character classification. To determine what methods to implement using such datasets, an average between the previously obtained accuracies and the ones using the same methods to the respective test sets was performed, shown in Table 2.

TABLE 2. Summary of handwritten letters classification accuracies.

	Digits		Letters	
	CNN	HOG-SVM	CNN	HOG-SVM
Subjects handwriting test	92.50%	97.50%	75.72%	73.32%
EMNIST testing set	99.34%	98.95%	92.51%	91.49%
Average	95.52%	98.23%	84.12%	82.41%

The best methods that were converted to C++ using MATLAB Coder to be implemented in the interface software were HOG-SVM for digit classification and a CNN for letter classification.

In the interface, as the user writes or draws something, the coordinates of the points of the trajectory of the tip of the haptic joystick pen are stored in vectors. Afterwards, a centered 28 by 28 pixels image is produced from the trajectory line, preserving the aspect ratio, maintaining a two white pixels wide border, along the edges. The drawn line is then thickened by iterating along rows and columns of the image and changing two neighbor pixels (one below and one to the left) to black upon finding a black pixel. The final image is then classified by HOG-SVM or a CNN, depending on whether it is a digit or a letter.

It is worth noting that MATLAB uses categorical data type to store data with a finite set of discrete categories to provide a more efficient storage and manipulation. This data type emerges, for example, when label extraction is performed by using the folder names in which the images are located (e.g., for training a CNN). As categorical is not a valid type for code generation, every categorical value was instead converted to double.

Important to note that only variations in coordinates x and y are considered. Variations in z coordinate were initially taken into consideration, given the use of the writing platform. Since the z coordinate of the platform plane is -60, points with a greater value than -60 (when the joystick pen is lifted above the platform) were deleted and would not be present on the image to classify.

Deleting points with a z value greater than -60 would remove relevant information (or even leaving an empty vector of coordinates) from the final image. Raising the point deletion threshold to a greater value (e.g., -50) would include unwanted points to a certain extent. However, and adding to this the fact that writing is a very personal task, and everyone has specific characteristics, such as tilt angle that not only vary interpersonally but also on the written character, changes in z coordinate were discarded and all the points are considered to perform transformation from coordinates to the final image.

C. DTW IMPLEMENTATION

As far as handwriting quality quantification is concerned, the first proposal was to use the score of the HOG-SVM/CNN classification. This would give an insight more about the method performance rather than the character quality, thus Dynamic Time Warping (making use of MATLAB Signal Processing Toolbox command DTW) was evaluated.

In this work, DTW is performed between the image (obtained from the user's handwriting) and a reference image of the same character. The trajectories of the reference images were developed using MATLAB and were stored in CSV files.

With the intention of enabling handwritten classification and evaluation, MATLAB functions were converted to C++ using MATLAB Coder. Upon each conversion, an example main function which declares and initializes data is generated. The functions present in the generated example were modified to fit the system needs, such as the inputs changed to vectors and the inclusion of the number of points of the trajectory as input so that the vectors could have the desired dimensions. As such, three functions, one for each of the methods (CNN, HOG-SVM and DTW), were converted, adapted, and implemented on the application software.

Other than including MKL-DNN library in the project, necessary changes were performed to the CPP files. For each classification method and for the evaluation method, a member function was created to allow the haptic device to be in the desired state (in this case WAITING). Changes were also carried out to the haptic joystick pen buttons callback member functions to take into consideration the member functions present in the respective CPP file.

To note that the classification methods, when converted using MATLAB Coder, use and define by default custom C++ data types for the respective variables (e.g., a dynamically allocated array of doubles is mapped to emxArray_real_T). As such, and to prevent conflict between type definitions of each classification method type in C++, MATLAB code was generated for multiple entry-point functions, one for each method.

The workflow is as follows: the system (in MainWindow CPP file) checks every second if any of the four Boolean variables (responsible for checking what method to perform, either digit or letter, training or evaluation) are true, as they are initialized as false. When a user clicks on any of the Train or Evaluate buttons, HapticManager sets the system state as waiting for user input. While the user is writing, the system is on its busy state. When the user finishes writing (by clicking on the lighter button on the haptic device pen), the respective Boolean variable is set to true, and the corresponding converted MATLAB routine is performed. The layout of the software interface is shown in figure 11. On the right-hand side of the figure, the users select the type of handwriting (namely letters or digits, with and without haptic guidance) they will perform and see the results of the classification.

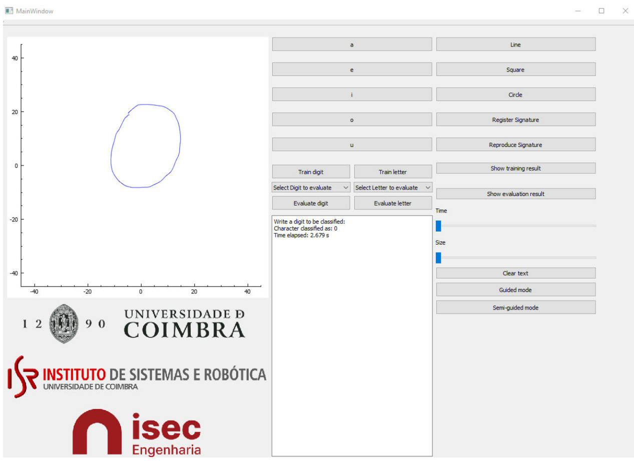

FIGURE 11. Interface showing a written digit zero, its classification and time elapsed.

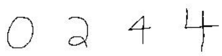

FIGURE 12. Images classified by HOG-SVM.

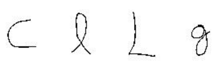

FIGURE 13. Images classified by a CNN.

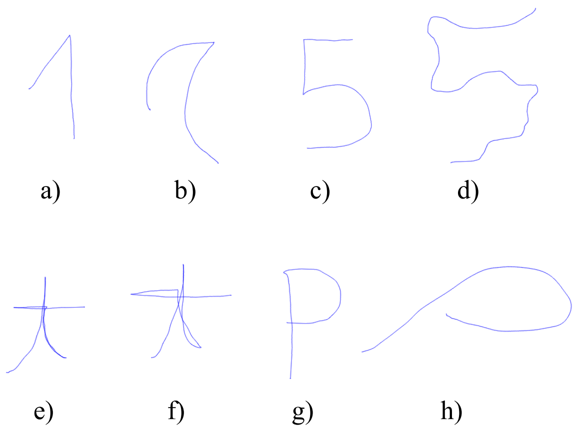

FIGURE 14. Plots of well written characters - a), c), e) and g) - and poorly written ones - b), d), f) and h), performed in the user interface.

TABLE 3. Handwritten character DTW evaluation.

Figure 14 Character		DTW	Diff	Figure 14 Character		DTW	Diff
'1'	a)	562.2	131.4	't'	e)	651.5	74.9
	b)	693.6			f)	726.4	
'5'	c)	806.0	43.9	'p'	g)	654.1	106.5
	d)	849.9			h)	760.6	

IV. RESULTS AND DISCUSSION

In this section, results from the classification of handwritten digits and letters, and quality of handwritten character evaluation using DTW are presented. Results on the haptic guidance impact in a handwriting retraining in rehabilitation scenario are also presented.

A. CLASSIFICATION

Random digits and letters were selected to conduct analysis on the system performance regarding character classification. Digit classification, making use of HOG-SVM, was performed to the numbers zero, two and four. Numbers zero, two and two different styles of number four (as shown in Fig. 12) were all correctly classified.

Regarding letter classification, using a CNN, the first character evaluated was uppercase C, which was also correctly classified. The second letter evaluated, lowercase l, was wrongly classified as an uppercase D. Its uppercase version, however, was rightly labelled. The last letter classified was lowercase g, which was also correctly labelled. The evaluated letters can be seen in Fig. 13.

Although only a limited number of characters were analyzed, it is visible that the developed system can be used to assess handwriting skills through character classification.

B. EVALUATION USING DTW

After performing classification tests, handwriting character evaluation using DTW was carried out. As explained previously, DTW is performed between the written character and a reference image of the same character.

Two versions (one well and another poorly written) of handwritten character '1', '5', 't' and 'p' were acquired, shown in figure 14 and the corresponding DTW evaluation is presented in table 3.

It can be clearly seen, from table 3, that the value obtained by the DTW for a well-written character is always lower. The difference of the DTW value (Diff) between the well-written character and the poorly written ones is higher for '1' and 'p', and in figure 14 it is possible to confirm that the poorly written characters '1' and 'p' are more poorly written than the poorly written characters '5' and 't'.

C. EVALUATION OF HAPTIC GUIDANCE RETRAINING

A DTW validation experiment was performed to evaluate if haptic guidance could be useful in a rehabilitation scenario (and if it could be measured through DTW distances). The experiment was composed of training sessions and test sessions. Every session was performed with the non-dominant hand to replicate a rehabilitation scheme.

The procedure sequence was:

1. Three initial testing sessions without haptic guidance;
2. Nine training sessions with haptic guidance;
3. Three final testing sessions without haptic guidance.

The first experiment was performed for lowercase letter a, example shown in Fig. 15.

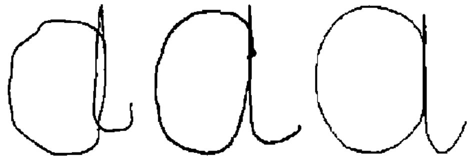

FIGURE 15. Test session example for letter a: before training (left), after training (center) and the reference letter used for training (right).

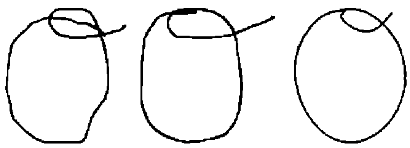

FIGURE 16. Test session example for letter o: before training (left), after training (center) and the reference letter used for training (right).

TABLE 4. Handwritten letters evaluation: DTW average distances before and after the training sessions.

	Before training	After training
Letter a	874.08 ± 67.74	841.96 ± 11.12
Letter o	935.12 ± 27.14	893.36 ± 20.70

The second experiment was performed for lowercase letter o, as shown in Fig. 16.

It is visible, from Fig. 15 and Fig. 16, that haptic feedback has an influence on the way the user writes the chosen character. Important to note that, unlike previous experiments, where the image size was of 28 by 28 pixels, the image size used for these experiments was of 224 by 224 pixels, as it gives better insight of image details and thickness variations along the images.

The next step consisted in performing DTW between every image before and after the training sessions, to see if the visual improvement could also be seen through DTW distances.

As stated before, DTW returns a sum of distances. Thus, as the DTW value decreases, handwriting quality increases, as the written character is closer to the reference image.

It is visible in Table 4 that there is a quality increase in the handwritten letters caused by the training sessions: for letter a, the average distance before training was 874.08 ± 67.74 and after training the distance decreased to 841.96 ± 11.12, leading to a 3.68% quality increase. For the letter o, the average distance was 935.12 ± 27.14 before training and 893.36 ± 20.70 after training, resulting in a 4.47% quality increase. Thus, DTW results are on par with visual inspection of both Fig. 15 and Fig. 16.

V. CONCLUSION AND FUTURE WORK

The system developed is composed by an application that allows both handwriting training through haptic guidance and handwriting assessment, which could be useful in a rehabilitation scenario, given the handwriting skills importance and its underlying skills.

Given the fact that there is no standard handwriting evaluation metric, DTW was tested and has shown to be adequate in performing comparison between users' handwriting (or between different rehabilitation phases of a user), and could be beneficial in dysgraphia diagnostics. Plus, comparison can be uniformized if there are standard reference images in a set size, like for example 224 by 224 pixels.

The system achieved its main purposes, which was both the creation of a haptic handwriting rehabilitation system, and handwriting classification and evaluation. Considering the haptic part of the rehabilitation system, the user can be guided through different character or geometric shapes trajectories and thus train handwriting in general. The user (or therapist) can also choose between guided mode, where the system guides the user to follow the trajectory, or semi-guided mode, where there is a virtual template through which the user can move the pen at his pace.

In relation to handwriting classification, specifically for digit classification, the used dataset was EMNIST Digits, and the employed method was HOG-SVM. This method achieved great results, partially because, in most cases, numbers are distinguishable from one another (i.e., have a different gradient orientation) and because there is generally just one way of writing numbers.

It was also proven that the choice of the dataset is relevant, as methods using MNIST presented lower classification accuracies when compared to the same methods using EMNIST Digits.

Letter classification method made use of EMNIST Letters and consisted in a CNN. The results were also satisfactory but slightly inferior when compared to digit classification results. This can be justified by a bigger number of possible outputs and by the fact that the dataset included both uppercase and lowercase versions of each letter in a single class, thus increasing intraclass variation and decreasing the method's accuracy. Training two networks, one for each version of the letter, would limit letter classification to be made separately but could be an advantageous approach in terms of labelling accuracy. Recent CNN models should also be considered as the ones used by Bhowmik [28].

Regarding handwritten characters evaluation, DTW was the chosen algorithm. The handwriting quality assessment tests not only confirmed DTW as a good method for this task, but also shows haptic feedback as being beneficial in a rehabilitation scenario, as tests performed after haptic guidance presented better results than those performed before haptic training. In this evaluation process, an image size of 224 by 224 pixels was used for improved accuracy.

Future work could focus on the creation of reference trajectories and respective images for all the letters (lower and uppercase) and numbers, and also on keeping track of the user evolution over time, creating a score that considers not only the DTW distance, but also the time taken to write the character (using, for example, reference times for each character). Other recent distance methods for handwriting quality assessment should be considered, namely ones based on AI techniques. A more complete evaluation process of the beneficial use of the haptic guidance in handwriting rehabilitation should be performed, namely by verifying the influence of the number of haptic guidance training sessions and by increasing the number of patients involved.

The system, as it stands, only uses haptic functionalities of the device for training lowercase vowels and some geometric shapes. Extending the use of these haptic functionalities to all the characters and guiding the user through a character upon achieving a low score on the evaluation of the same character, would increase the user independence during rehabilitation. At the time, this process can only be done if a therapist uses the Register Signature button, and the user follows what the therapist wrote using the Reproduce Signature button.

In summary, the system developed herein exhibited positive results not only in haptic guidance and training, but also in handwriting analysis by classifying and evaluating user input. As it stands, the system can already be used to assess handwriting skills and has proven to be scalable on a handwriting and hand therapy standpoint, as it could contribute to writing skills rehabilitation through training, classification, and evaluation.

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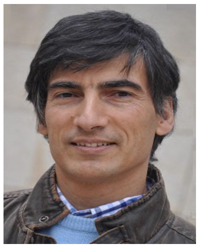

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