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# LINFO2275 : project 2

Hand gesture recognition

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# 1 Introduction

We want to implement a hand gesture recognition system for a smart user interface. A 3D tracking of the position vector  $\tilde{\mathbf{r}}(t) = (x(t), y(t), z(t))^T$  of the hand is recorded as a sequence of the 3 coordinates in function of the time  $t$ <sup>1</sup>. The user is executing a sketch that is recorded and recognized by the system.

The system will be trained in order to recognize two different kind of sketches.

A first dataset contains the records of the numbers 0, 1, 2, 3, 4, 5, 6, 7, 8, 9 in three dimensions. We asked 10 users to draw 10 times each of these numbers. We have therefore a total of 1000 sequences.

A second dataset contains the records of three-dimensional figures. As for the precedent dataset, 10 users have drawn each figure 10 times.

## 2 Preprocessing

We first preprocessed the data. We embedded the datas in a list of 1000 entries. Each entry consist in a matrix of dimension  $(n\_timepoints, vec\_dimensions)$  where  $n\_timepoints$  is the length of the time series and  $vec\_dimensions$  is the dimension of the position vector which is 3 in our case. Notice that each time series has different length, that's important for what is to follow. After that, we resampled each time series into  $N = 64$  points for the DTW algorithm and into  $N = 32$  points for the \$P\$-Recognizer algorithm by performing interpolation. Indeed, performing vector-quantization using a k-means algorithm gave us poor results so we chose to resample by interpolation as proposed in the following article. This article claim to resampling time series into 32 to 64 points gives good results. We notice it was also the case for the DTW algorithm and choose to limit ourself to 32 points for the \$P\$-Recognizer algorithm as resampling into more points implies too long computation time.

## 3 Dynamic time warping

### 3.1 Introduction

Given a time series of three-dimensional unknown vector data points, we would like to predict the sketch represented by these points. In order to do this, we used a K-Nearest Neighbors approach where we find the  $k$  most similar time series in the dataset and use the most represented target value among the  $k$  time series and use it as the prediction output.

To find the  $k$  most similar time series, we use a distance function as the similarity measure. However, we cannot use the often used euclidean distance as it produces pessimistic results when dealing with time series of different lengths.

Dynamic time warping - a often used technique in speech recognition problem - is a solution to this problem, it finds the optimum alignment between two time series by "warping" non-linearly a time series stretching or shrinking its time axis. Once we found the optimal alignment, we can determine the similarity between these twos.

Let  $s = (s_1, \dots, s_n)$  and  $t = (t_1, \dots, t_m)$  be two time series of length  $n$  and  $m$  respectively where  $s_i, t_j$  are the position vector  $\in \mathbb{R}^3$  for  $i = 1, \dots, n$  and  $j = 1, \dots, m$ . We define a warping of order  $n \times m$  as a sequence of  $k$  points  $x = (x_1, \dots, x_k)$  where  $x_l = (i_l, j_l) \in [1, n] \times [1, m]$ . Each points  $x_l$  of the path aligns the vector  $s_{i_l}$  with the vector  $t_{j_l}$ .

The following constraints apply,

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1. Note that we will not consider the precise recorded time of the observations.

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- **boundary conditions** :  $x_1 = (1, 1)$  and  $x_k = (n, m)$ . This ensures that every index of the time series are used in the warp path.
  - **locality** :  $x_{l+1} - x_l \in \{(1, 0), (1, 1), (0, 1)\}$ ,  $\forall l \in [1, k - 1]$ .

The locality condition implies a monotonicity condition :  $s_1 \leq \dots \leq s_n$  and  $t_1 \leq \dots \leq t_m$ . This monotonicity implies that the lines representing the warp path do not overlap.

Among all the warping path we can construct, want to find the optimal warping path  $x^*$  that consists in the warping path that minimizes the square root of the following cost given for any warping path  $x$ ,

$$C_x(s, t) = \sum_{l=0}^k \|s_{i_l} - t_{j_l}\|_2^2 \quad (1)$$

We can then compute the DTW distance by computing the total cost of the warping path  $x^*$ .

In practice, to find the optimal path, we use a dynamic programming approach which consists in the following algorithm,

1. We define a distance matrix  $D \in \mathbb{R}^{n \times m}$  where  $D_{i,j}$  is the minimum-distance for the warping path between  $s' = (s_1, \dots, s_i)$  and  $t' = (t_1, \dots, t_j)$ .
2. Each entry is computed by using the following recursion formula,

$$D_{i,j} = \sqrt{\|s_i - r_j\|} - \min(D_{i-1,j}, D_{i-1,j-1}, D_{i,j-1}) \quad (2)$$

with the initial condition  $D_{1,1} = 0$

3. The entry  $D(n, m)$  contains the minimum-distance for the warping path between  $s$  and  $t$ .

This algorithm has  $\mathcal{O}(nm)$  time complexity. We can however speed up the algorithm by applying **constraints** that consists in limiting the number of cells that are evaluated in the distance matrix (e.g. using a Sakoe-Chiba Band window<sup>2</sup>) and **data abstraction** that consists in performing the algorithm on a reduced representation of the data. Instead of running the algorithm on the full distance matrix, we reduce the size of the time series which implies that the number of cells in the distance matrix are reduced. Once the warping path is found on this low-resolution matrix, we map it back to a higher-resolution matrix. This projected path is used as an initial guess for a new warping path on this new distance matrix. In other words, the projected path is refined on the higher-resolution matrix by making **local adjustments**<sup>3</sup> which implies that this matrix is only filled in the neighborhood projected path. This results in a algorithm with linear time complexity since the warping path grows linearly with the size of the time series.

Researches **keylist** have shown that using a single neighbor in the KNN algorithm gives the best results. Moreover, trying different combination of number of neighbors and radius hyperparameters, we notices that a good tradeoff between efficiency and rapidity was not only obtained with a single neighbor but also with a radius of 1.

## 3.2 Results

### 3.2.1 User-independent cross-validation

In the user-independent cross-validation, for the first domain, we get a mean accuracy of 0.743 with a large standard deviation of 0.146. Interestingly, looking at the confusion matrices for the different splits, we notice a lot of misclassifications for the last split.

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2. In a nutshell, this window assumes that the best path will not stray too far away from the main diagonal of the distance matrix.

3. These local adjustments can be controlled through a radius parameter that controls the number of cells that will be evaluated around the path.

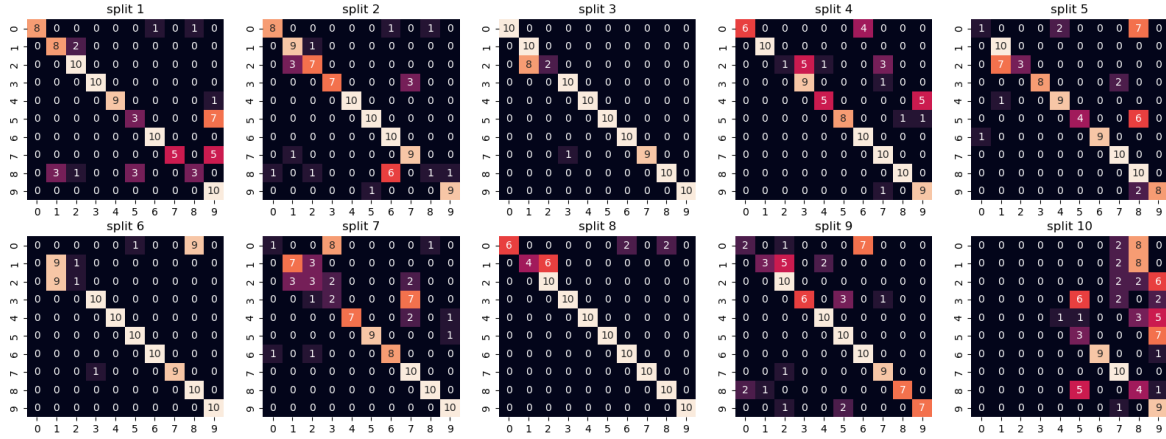


FIGURE 1 – Confusion matrices of the different splits for the domain 1 using fast DTW algorithm (user independent cross-validation)

For the third domain however, we get a mean accuracy of 0.853 with still a large standard deviation of 0.117. It was pretty much unexcepted as this domain contains (plus complexes) sketch than simple numbers. Here it is the split nine that contains a lot of missclassifications

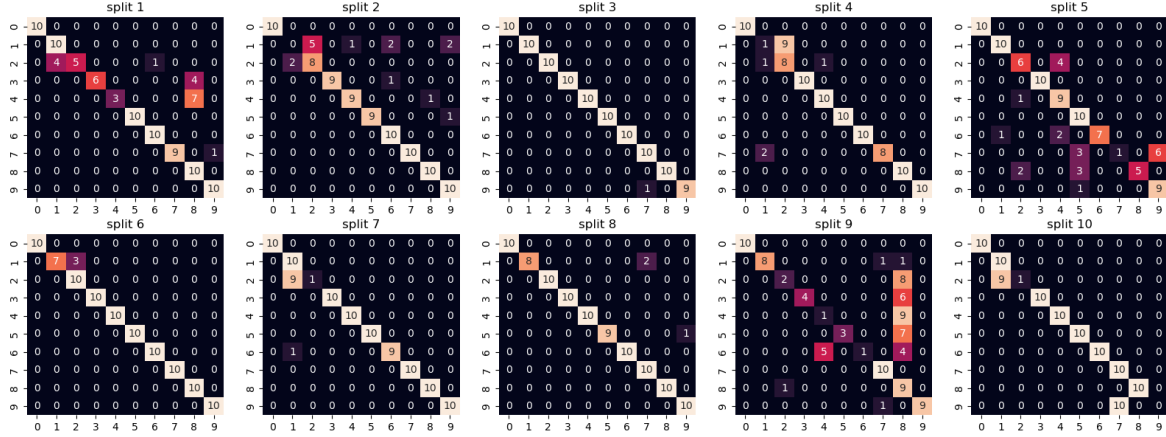
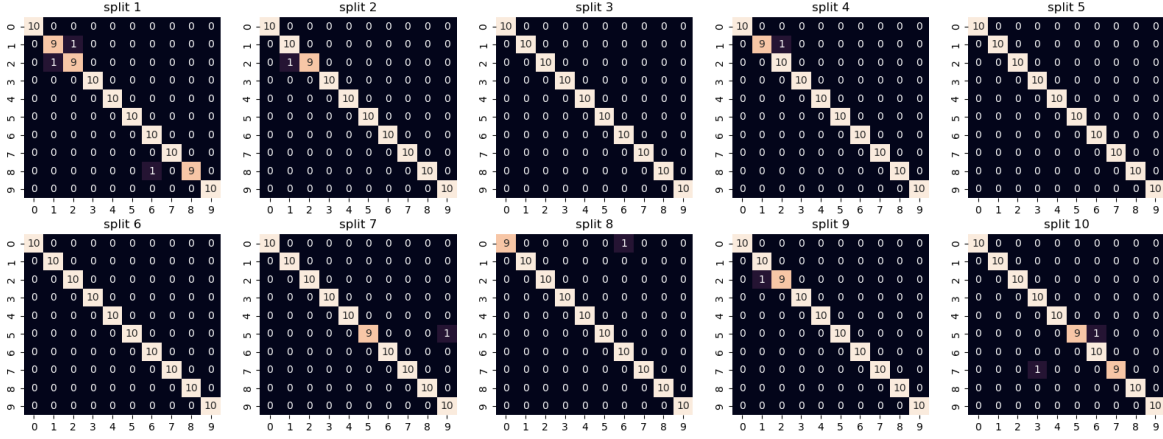


FIGURE 2 – Confusion matrices of the different splits for the domain 3 using fast DTW algorithm (user independent cross-validation)

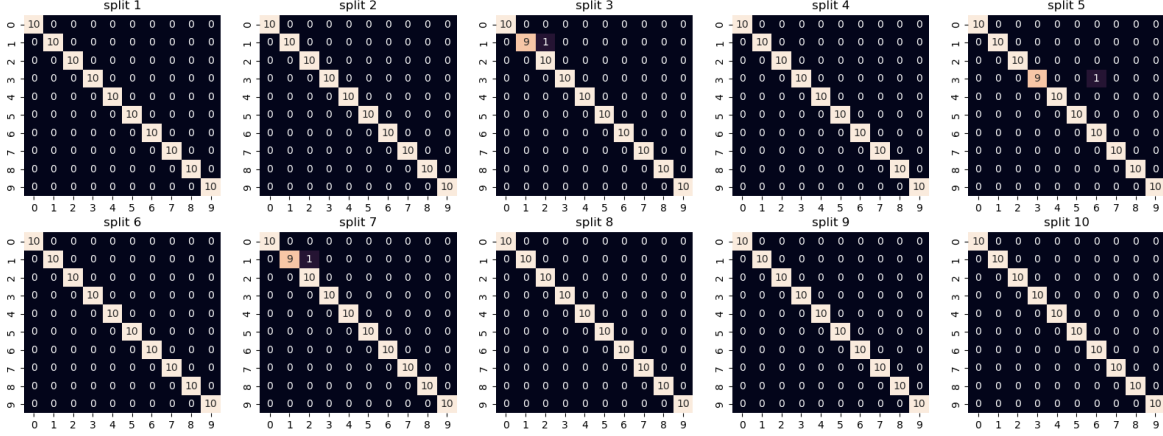
### 3.2.2 User-dependent cross-validation

In the user-dependent cross-validation, we get far more better results. For the first domain, our classifier is almost perfect with a mean accuracy of 0.99 and a standard deviation of 0.009.



**FIGURE 3** – *Confusion matrices of the different splits for the domain 1 using fast DTW algorithm (user dependent cross-validation)*

For the third domain, we have a mean accuracy of 0.997 and a standard deviation of 0.005.



**FIGURE 4** – *Confusion matrices of the different splits for the domain 3 using fast DTW algorithm (user dependent cross-validation)*

## 4 \$P\$-recognizer

In this algorithm, we consider each gesture as a set of points :  $\{p_i = (x_i, y_i) : i = 1, \dots, N\}$ . In our case, because of the resampling made in the preprocessing step, each gesture is represented by a set of  $N = 64$  points. It is worth noticing that gesture are seen as a cloud of points so that there does not need to have order in the set (i.g.  $p_1$  is not the starting point nor  $p_i$  follow  $p_{i-1}$ ) even though it's the case for us.

Let  $C$  and  $T$  be clouds of points. The first one correspond to a gesture candidate whereas the second one is a template in the training set. The aim of this algorithm is to match  $C$  to  $T$  by the use of a nearest neighbor classifier (KNN) in the same idea as in the precedent section. Here we obviously do not use a DTW algorithm to compute the distance but the sum of euclidean distances for all pairs of points

$(C_i, T_j)$  where  $C_i \in C$  is matched to  $T_j \in T$  through some function  $f : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ ,  $C_i \rightarrow f(T_j)$ ,

$$d(C, T) = \sum_{i=1}^N \|C_i - T_j\|_2 \quad (3)$$

However this algorithm require to search for the minimum matching distance between  $C$  and  $T$  from  $n!$  possible alignments. The library we used to run this algorithm use a special heuristic called Greedy-5keylist. The idea is that for each point  $C_i \in C$ , we find the closest point in  $T$  that has not been matched yet. Once it is matched with  $C_i$ , we continue with  $C_{i+1}$  and so on until all the points of  $C$  are matched with a point of  $T$ . The closeness is computed through a weighted euclidean distance,

$$d(C, T) = \sum_{i=1}^N w_i \|C_i - T_j\|_2 \quad (4)$$

where  $w_i$  indicate the confidence in each pair  $(C_i, T_j)$ .

Basically, the first match has a weight of 1 since  $C_i$  has all the points of  $T$  to choose for the closest match. As long as the possibility of matching reduce, the confidence also. The formula for the weights translate a linearly decreasing weighting,

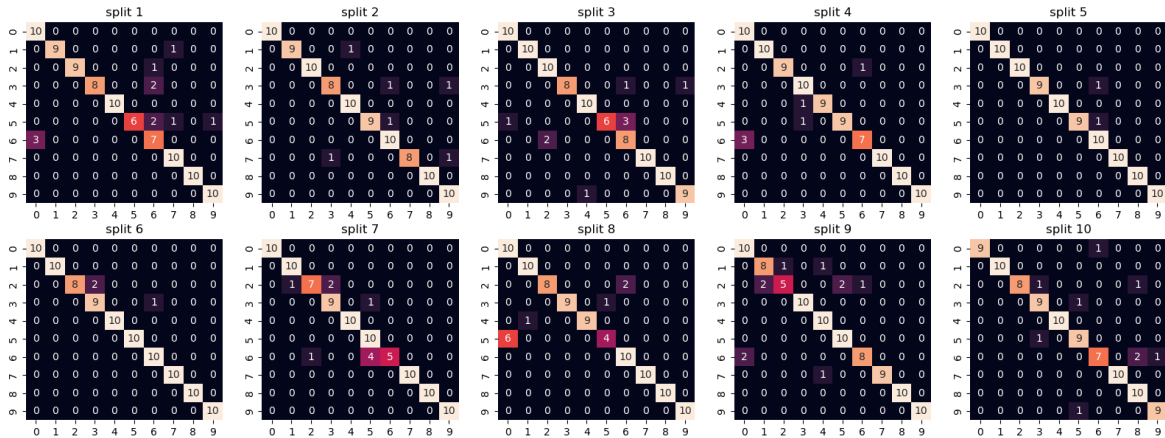
$$w_i = 1 - \frac{i - 1}{N} \quad (5)$$

This heuristic allows us to have a time complexity of  $\mathcal{O}(n^{2+\epsilon})$  which is comparable to the DTW algorithm without any optimization.

## 4.1 Results

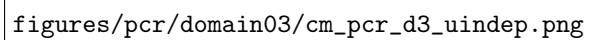
### 4.1.1 User-independent cross-validation

For the first domain, we get a mean accuracy of 0.925 along with a standard deviation of 0.029 for the user-independent cross-validation. This is way better than with the DTW algorithm even though we had resample the datas with half the number of data points than for the precedent algorithm for computation time purpose.



**FIGURE 5** – Confusion matrices of the different splits for the domain 1 using  $\$P$ -Recognizer algorithm (user independent cross-validation)

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The figure area is mostly blank, with the file path 'figures/pcr/domain03/cm\_pcr\_d3\_uindep.png' printed in the lower-left corner. This indicates that the confusion matrices for the different splits of domain 3 using the \$P\$-Recognizer algorithm (user independent cross-validation) are not visible in this rendering.

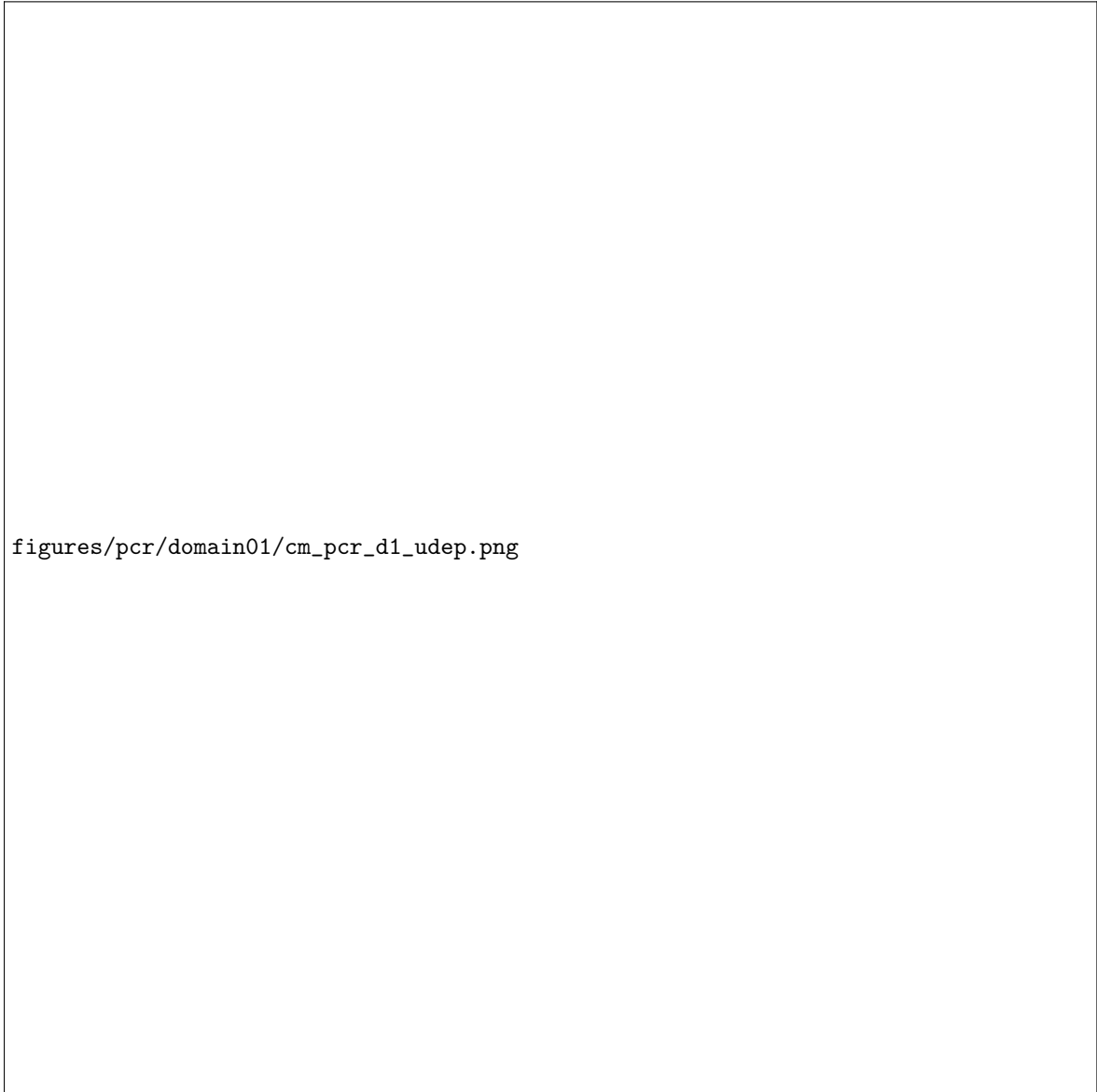
**FIGURE 6** – *Confusion matrices of the different splits for the domain 3 using \$P\$-Recognizer algorithm (user independent cross-validation)*

#### 4.1.2 User-dependent cross-validation

For the first domain, we get a mean accuracy of 0.967 with a standard deviation of 0.02. This is a little bit more accurate than for the user-independent cross-validation



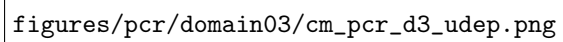
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figures/pcr/domain01/cm\_pcr\_d1\_udep.png

**FIGURE 7** – *Confusion matrices of the different splits for the domain 1 using \$P\$-Recognizer algorithm (user dependent cross-validation)*

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figures/pcr/domain03/cm\_pcr\_d3\_udep.png

**FIGURE 8** – *Confusion matrices of the different splits for the domain 3 using \$P\$-Recognizer algorithm (user dependent cross-validation)*

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## Appendix