RECURSIVE CLUSTERING ALGORITHM FOR THUMB MOTION CLASSIFICATION

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Abstract: This paper deals with recursive algorithm used for the clustering of the stationary states in three-dimensional thumb motion signal. The thumb motion is parameterized tracing a special mark on the thumb. This algorithm is based on computing of distances between each subsequent positions of the mark. The pair of positions with the smallest distance are merged into one centre in each iteration. Thus the length of the thumb motion signal is reduced by one term. The recursion is stopped if the number of clusters is appropriate.

The algorithm is used in biomedical engineering for research on correlations between a finger motions and a human brain function.

Introduction

Presented clustering algorithm is a part of a procedure used for parameterization and classification of thumb motions. This procedure is used for a research of correlation between human body motions and a human brain activity.

Due to a complexity of human brain function the free three-dimensional motion of thumb as a sample of a simple body motion has been chosen. The muscle activity is represented by the parameters of the thumb trajectory, the brain activity is represented by the electroencephalograph (EEG) signals.

The parameters of thumb trajectory are obtained from 3-D parameterization process. The thumb is marked by special mark. The thumb motion is sensed using the pair of standard DV camcorders. The outputs of recording are two video sequences in PAL standard (720×526 pixels, 25 frames per second) stored on a tape. The thumb motion is parameterized tracing the mark [1].

Methods

The aim of the presented algorithm is to find the stationary states in the thumb motion record and to substitute each one with corresponding average value.

The thumb trajectory is represented by the matrix $\boldsymbol{C}_{ik}$, where i is the dimension index ($i = 1$ for one dimensional data and $i = \{1,2,3\}$ for the three dimensional data) and the k is the frame index [2]. Each column of this matrix represents the thumb position (thumb motion coordinates) in the frame k.

The presented clustering algorithm is recursive and it is described in steps below.

Step 1 Initialization of the variables

The iterative index n, the mass centres signal $\mathbf{C}_{in}[k]$, the time index signal $t_n[k]$ and the weights signal $w_n[k]$ are initialized firstly.

$$\begin{aligned} n &= 0 \\ t_0[k] &= k \\ \boldsymbol{C}_{i0}[k] &= \boldsymbol{C}_{ik} \\ w_0[k] &= 1 \end{aligned} \tag{1}$$

Step 2 Initializing of the next iteration

$$\begin{aligned} \boldsymbol{C}_{i(n+1)}[k] &= \boldsymbol{C}_{in}[k] \\ t_{(n+1)}[k] &= t_n[k] \\ w_{(n+1)}[k] &= w_n[k] \end{aligned} \tag{2}$$

Step 3 Computing the mass centres distances

$$d_n[k] = \sqrt{\sum_i (\boldsymbol{C}_{in}[k+1] - \boldsymbol{C}_{in}[k])^2} \tag{3}$$

Step 4 Merging the mass centres

The time index K, for which $d[k]$ is minimal, is found in this step.

$$K = \arg\min_k d_n[k] \tag{4}$$

For this K the equations below are computed. It means, that the closest mass centres are merged and substituted by one mass centre.

$$\begin{aligned} \boldsymbol{C}_{i(n+1)}[K] &= \frac{\boldsymbol{C}_{in}[K]w_n[K] + \boldsymbol{C}_{in}[K+1]w_n[K+1]}{w_n[K] + w_n[K+1]} \\ t_{(n+1)}[K] &= \frac{t_n[K]w_n[K] + t_n[K+1]w_n[K+1]}{w_n[K] + w_n[K+1]} \\ w_{(n+1)}[K] &= w_n[K] + w_n[K+1] \end{aligned} \tag{5}$$

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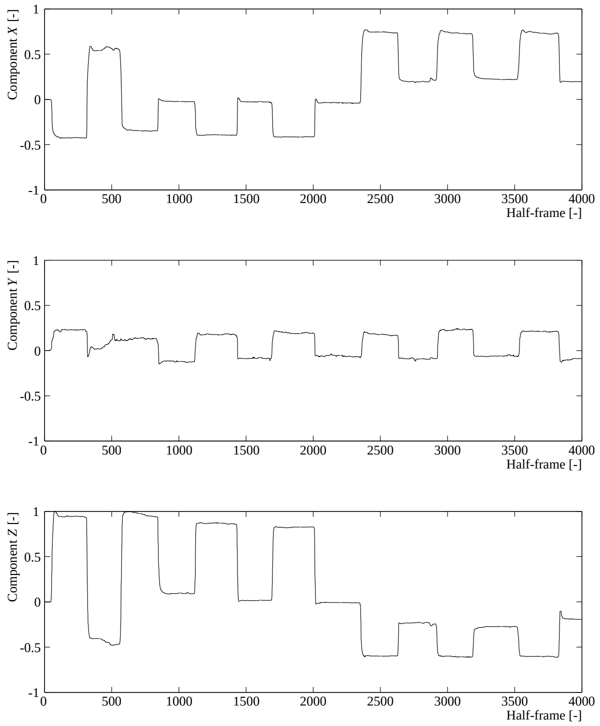

Figure 1: The input signal

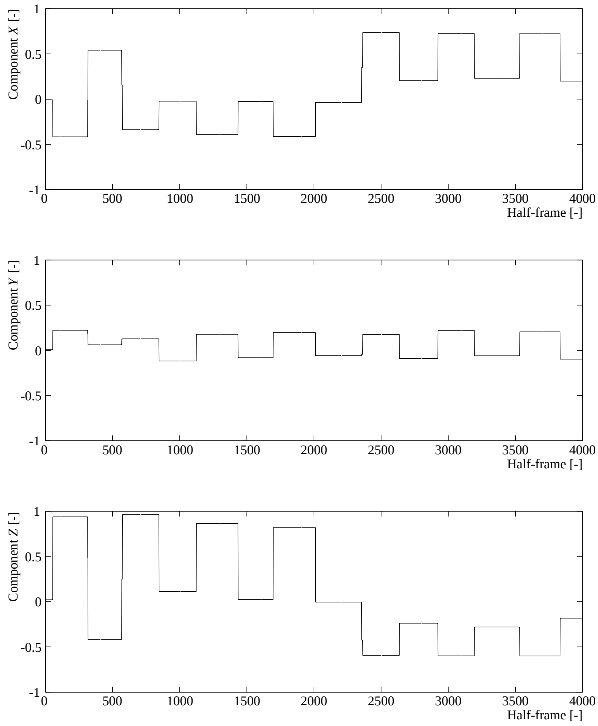

Figure 2: The processed signal

Step 5 Omitting of the merged mass centre

The terms $\mathbf{C}_{i(n+1)}[K+1]$, $t_{n+1}[K+1]$ and $w_{n+1}[K+1]$ are omitted. It means, that the lengths of the sequences are decreased by one.

Step 6 Repeating the recursive process

The iterative index n is increased by one and the recursive process continues by the step 2 until the length of the mass centres signal is not appropriate.

Results

Presented method was used for clustering of the set of input data. The input signal was acquired during the experiment. The sensed person moves thumb between 4 positions. Each move is triggered with optical synchronization pulse [3] . The period of synchronization pulses is 6 ± 1 seconds.

So the input signal includes the 4 stationary states and the transitions between these states. The period of the transitions is approximately 300 samples, it corresponds to 6 seconds (300 half frames in PAL TV standard) in real motion. The lengths of stationary states are approximately 280 samples, the lengths of transitions are 20 samples, directions of the transitions are chosen randomly by the sensed person.

The section of the input signal – the short segment of the motion projections to the axes x, y and z – is shown in figure 1. This section has 4000 samples and it was processed using the presented algorithm to 18 clusters. The computed values $x[k]$, $y[k]$, $z[k]$, $t[k]$ and $w[k]$ are shown in table 1 and the processed signal is shown in figure 2.

Conclusions

The recursive clustering algorithm has been described in this paper. Presented algorithm is similar to agglomerative hierarchical clustering method([4], [5], [6], [7]). The main difference is that the distances between samples in

Table 1: The results of clustering process

k	$x[k]$	$y[k]$	$z[k]$	$t[k]$	$w[k]$
1	-0.01	0.01	0.02	27.5	55
2	-0.42	0.22	0.94	186.0	262
3	-0.01	0.19	0.48	318.0	2
4	0.54	0.06	-0.42	444.5	251
5	0.16	0.12	0.25	572.5	5
6	-0.34	0.13	0.96	711.0	272
7	-0.02	-0.12	0.11	986.0	278
8	-0.39	0.18	0.86	1280.5	311
9	-0.03	-0.08	0.02	1566.5	261
10	-0.41	0.20	0.82	1854.5	315
11	-0.04	-0.06	-0.01	2184.0	344
12	0.35	-0.04	-0.43	2360.0	8
13	0.74	0.18	-0.59	2500.5	273
14	0.20	-0.09	-0.24	2780.5	287
15	0.72	0.22	-0.60	3059.5	271
16	0.23	-0.06	-0.28	3364.0	338
17	0.73	0.21	-0.60	3683.5	301
18	0.20	-0.10	-0.18	3917.0	166

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input signal are computed for subsequent samples using this algorithm (step 3), but in the standard hierarchical clustering algorithm the distances are computed for each by each samples. This modification rapidly decreased the memory demands, because we have to compute only $N-1$ distances for the N samples using presented algorithm instead of N^2 distances using the standard hierarchical clustering algorithm.

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References

[1] Jan Havlík and Zdeněk Horčík. Three-dimensional thumb motion parameterization. In *Applied Electronics 2005*, pages 127–130. University of West Bohemia in Pilsen, Pilsen, 2005.

[2] Jan Havlík and Zdeněk Horčík. Finger motion parameterization based on image processing. In *Biosignal 2004*, pages 321–323. VUTIM Press, Brno, 2004.

[3] Jan Havlík and Zdeněk Horčík. Synchronization of EEG and video signals (in Czech). In *Matlab 2004*, pages 186–189. Humusoft, Prague, 2004.

[4] William H. E. Day and Herbert Edelsbrunner. Efficient algorithms for agglomerative hierarchical clustering methods. *Journal of Classification*, 1:7 – 24, 1984.

[5] Stephen C. Johnson. Hierarchical clustering schemes. *Psychometrika*, 32(3):241 – 254, 1967.

[6] Andrew W. Moore. K-means and hierarchical clustering [online].
URL: <http://www.autonlab.org/tutorials/
/kmeans.html>, [2005-09-14].

[7] Alena Lukasová and Jana Šarmanová. *Methods of Cluster Analysis (in Czech)*. SNTL, Praha, 1985.

[8] P. Allard, I. Strokes, and J-P. Blanchi. *Three Dimensional Analysis of Human Movement*. Human Kinetics, 1995.

[9] T. Andriacchi and E. Alexander. Studies of human locomotion: past, present and future. *Journal of Biomechanics*, 33:1217 – 1224, 2000.

[10] G. Baroni et al. Implemantation and application of real-time motion analysis based on passive markers. *Medical and Biomedical Engineering Computing*, pages 693 – 703, 1998.

[11] N. A. Borghese and G. Ferrigno. An algorithm for 3–D automatic movement detection by means of standard TV cameras. *IEEE Transaction of Biomedical Engineering*, 37:1221 – 1225, 1990.