Abstract: This work focuses on the dynamic time warping for vehicle classification. The theoretical part includes the dynamic time warping algorithm description. The DTW module in Python, that was created during this work, is subsequently applied for the recognition of vehicle types by their side profiles based on the DTW.

Keywords: dynamic time warping, vehicle classification, vehicle side profile

1 INTRODUCTION

Dynamic time warping algorithm is a simple method used for non-linear comparison of two sequences. Theoretically, it can be used for everything that can be expressed in the form of a sequence of numbers or characters. The modern world is digital and DTW has very wide range of applications. In particular, it is often used in the areas of speech recognition, bio-medicine, recognition of signatures and manuscripts, sequential pattern mining and recognition of body movements or gestures. The following paper examines the application of this method for the recognition of vehicles by their profiles.

2 DTW

DTW inputs are two sequences $r \in \mathbb{R}^M$ and $q \in \mathbb{R}^N$. The following local cost matrix is computed on the basis of the selected metrics $c : X \times X \rightarrow \mathbb{R}$:

$$C \in \mathbb{R}^{M \times N}, c_{ij} = c(r_i, q_j)$$

(1)

The transformation path is a sequence of points $p = (i_k, j_k) \in [1 : M] \times [1 : N]$ for $k \in [1 : l]$. The cost of the path $C_p \in \mathbb{R}$ is defined as a sum of all the local cost matrix elements in the path.

The optimal path is the path with the minimum cost. The optimal path can be found using the brute force in exponential time. In DTW the dynamic programming is used instead so the complexity decreases to $O(MN)$. The algorithm maps the local cost matrix to a global cost matrix in the following way. Local matrix is expanded by one row and one column: $C(0 : M, 0) = \infty$ and $C(0, 0 : N) = \infty$. The first element in the global matrix is defined as $D(1, 1) = C(1, 1)$. The remaining elements are calculated as follows:

$$D(i, j) = \min \{D(i - 1, j), D(i, j - 1), D(i - 1, j - 1)\} + c(r_i, q_j)$$

(2)

Key feature of the global cost matrix is that each of its elements expresses the cost of the optimal path of sequences sliced to the position of this element in the matrix. Thus:

$$D(i, j) = \min \{C_p(r(1 : i), q(1 : j))\}$$

(3)

The output from DTW is the cost of the optimal path, so it is the last element of the matrix $D$. The path can be found by the steepest descent from point $D(M, N)$ to point $D(1, 1)$. 

156
3 DTW LIBRARY

The dynamic time warping library was programmed during this work. The library is written in Python and the computational core is written in C. There are several ways to connect the Python and C languages. The DTW library uses Cython, which is a programming language that has the syntax very similar to Python's. However, unlike Python, the Cython code compiles and has a static typing. Cython also makes it easy to call back and forth from and to C or C++ code. Figure 1 shows the structure of the library. Computational part is located in the cdtw.c. The dtw.pyx is the interface for Python written in Cython. From files cdtw.c and dtw.pyx Cython compiler generates dtw.c – C-code that already contains a Python API. C compiler(GCC) then generates a shared library dtw.pyd which can be imported to Python code.

![Diagram of relations between C, Python and Cython code](image)

Current library contains 3 step functions, 5 types of global constraints, normalization and the tools for graphical representation of the results. The speed is about 25ms for the sequences with the length of 1000 elements and about 1.6s for 8000 elements. Testing was performed on a 1.8 GHz Intel i5-3337u (boost to 2.7 GHz) and the operating system Windows 8.1.

4 DTW FOR VEHICLE CLASSIFICATION

During this work, time warping method has been applied to profiles of vehicles – real data from a 3D scanner. Camea Ltd. provided data(24-hour traffic), which contains:

- records from 3D laser scanner SICK
- records with weight, speed, number of shafts and the vehicle length - WIM
- vehicles photos

The database was created from this data. Every sample contains the profile of vehicle, the type and identification number according to the time when the vehicle has been recorded. At the moment the database contains 757 samples. A profile of the vehicle is defined as a maximum transverse height. 100 runs of the holdout method using stratified sampling and k-NN model were used to estimated the classification performance. During each run one third of data is used for training and the remaining data for testing.
We have not found a better setting than the classical DTW. The usage of the windows, step functions other than equation 2, normalization by the transformation path length or by the normalization factor had a negative impact on the classification results. The best result had been achieved by k-NN with \( k = 3 \) and the classical DTW.

Table 1: The number of vehicles in database

<table>
<thead>
<tr>
<th>type of vehicle</th>
<th>quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>car</td>
<td>420</td>
</tr>
<tr>
<td>van</td>
<td>84</td>
</tr>
<tr>
<td>lorry</td>
<td>49</td>
</tr>
<tr>
<td>truck</td>
<td>193</td>
</tr>
</tbody>
</table>

Table 2: The classification results

<table>
<thead>
<tr>
<th>type of vehicle</th>
<th>FPR[%]</th>
<th>FNR[%]</th>
<th>ACC[%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>car</td>
<td>0,78</td>
<td>3,17</td>
<td>97,88</td>
</tr>
<tr>
<td>van</td>
<td>3,12</td>
<td>5,98</td>
<td>96,56</td>
</tr>
<tr>
<td>lorry</td>
<td>1,03</td>
<td>18,88</td>
<td>97,79</td>
</tr>
<tr>
<td>truck</td>
<td>0,37</td>
<td>2,47</td>
<td>99,08</td>
</tr>
</tbody>
</table>

5 CONCLUSION

This paper describes the DTW library for Python. It contains several popular types of step functions and global constraints. It also contains some graphical tools. DTW algorithm had been applied on the profiles of the vehicles – real data from a 3D scanner. Two interesting conclusions are worth to emphasize. First the simple point laser distance sensor and DTW could be used instead of 3D laser scanner while achieving high classification performance comparable to some commercial solutions but with lower cost. Second when limited to the task of vehicle type classification the suggested solution achieves comparable results to some commercial camera based systems. The laboratory model, aiming to imitate the process, is in the phase of development at the moment.

REFERENCES

