Temporal and Longitudinal Variances in Wood Log Cross-Section Image Analysis

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INTRODUCTION

Traceability of wood logs is a basic requirement to fullfill econmical, social and legal requirements and state-of-the art methods require physical marking of each log.

Another approach comes down to identify logs using biometric log characteristics. We assume that logs can be identified based on biometric features extracted from the annual ring patterns from digtital images of log ends. This first study on biometric log recognition using log end images investigates if this approach is robust to two practical issues which arise in a real world application: Temporal and longitudinal variances of wood log cross-sections (CSs).

Temporal variances (Fig. 2) are caused by light and humidity and result in deformations like cracks and discolourations. Longitudinal variances (Fig. 1) result from log end cutting or from capturing different log ends.

For our investigations the FingerCode approach by Jain et al. (2000) is adopted to compute CS codes and matching scores between CS images.

TESTSET

Our experimental evaluation is based on 35 CS slices which were cut from two sections of a single tree log. Each slice was captured four times with different time spans inbetween.

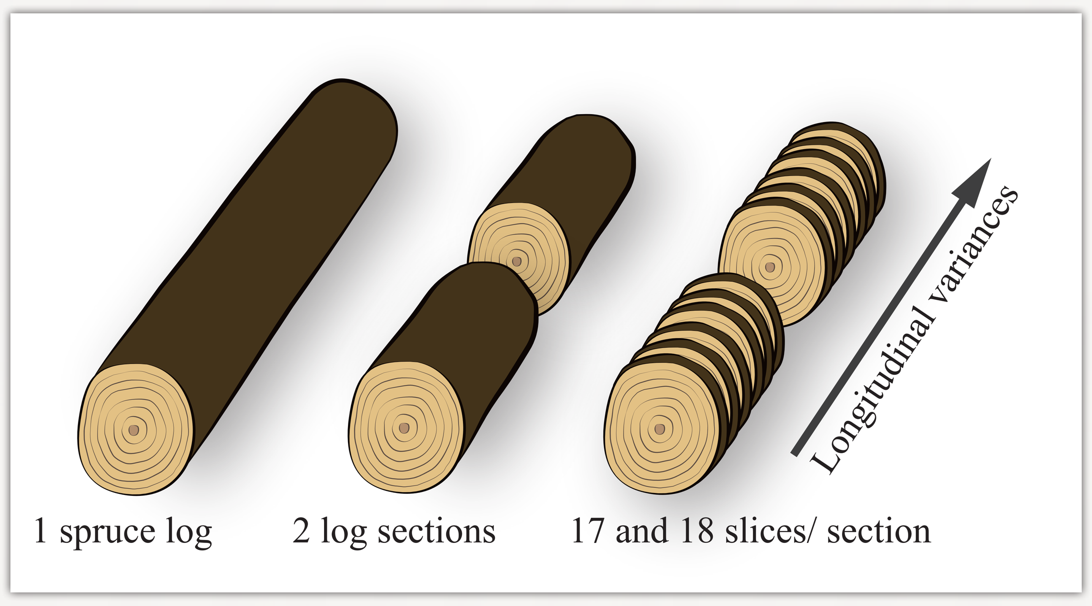

Figure 1. Illustration of the testset creation procedure

Figure 2. Testset example: Slice #10 -Section 2 / Sessions 1−4. The four CS images illustrate the temporal variances between the time delay captured images of Session 1−4.

CS-CODE COMPUTATION AND MATCHING

For the computation of a CS-Code the input image is registrated according to the CS border and a certain rotation and is scaled to 512 pixels in width. Subsequently, the registrated image is enhanced by local adaptive filtering annual ring pattern patches using Log-Gabor filters.

Finally, a Gabor filterbank is used to capture local orientation and frequency information from the annual ring pattern. Rotational variances are compensated by repeatedly computing a CS-Code for rotated versions of the input CS image.

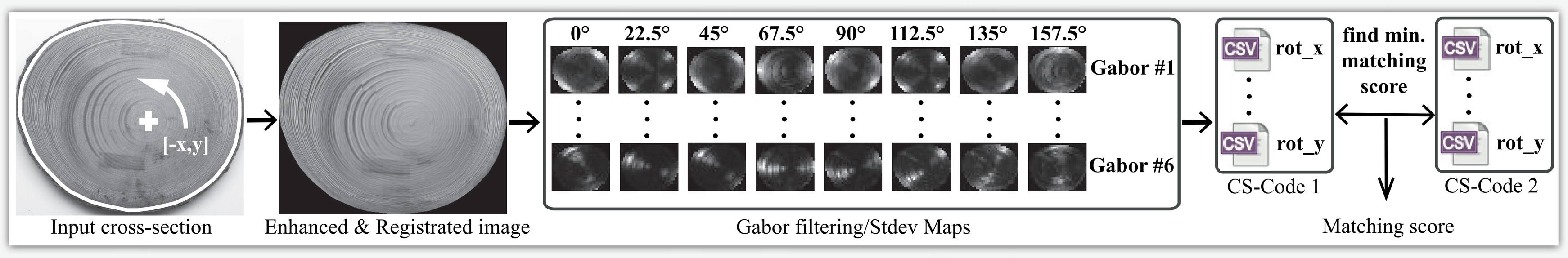

Figure 3. CS-Code computation and matching scheme

The matching score between two CS images is computed by determining the minimum matching score between all computed CS-Codes from two CS images. The matching score between two CS-Codes can be computed with a set of distance metrics.

MAIN RESULTS

- Results indicate that a biometric system using log end images is robust to issues caused by environmental influences and log length cutting.
- With an increasing time span between two CS images of the same CS the CS-Code distance increases too.
- Adjacent CS slices show low CS-Code distances and the CS-Code distances increase with an increasing distance between two CS slices.

EXPERIMENTS AND RESULTS

The matching scores computed between all CS images are used to compute temporal and longitudinal variances and in addition, interclass variances are simulated. For each distance metric and the different variances the corresponding matching score distributions (SDs) are created. Table 1 shows the intersections between the temporal / longitudinal SDs and the interclass-SD. The lowest overlaps between the temporal and longitudinal SDs and the interclass SD are reached using the L_1 norm (see Fig. 4).

Distance Metric	Temp-Long	Temp-Inter	Long-Inter
EMD	82.25%	24.66%	33.00%
L_1	68.51%	1.31%	6.00%
L_2	72.10%	3.77%	14.00%
2D-matching	67.53%	2.86%	13.00%

Table 1. Intersections of the score distributions (SDs) for different distance metrics

Temporal Variances:

The stacked area chart in Fig. 5 illustrates the subset structure of the temporal SD (L_1 norm). The labelled subset areas illustrate the proportions of the matching scores between different sessions. Overall the highest CS-Code distances arise in subsets where one session is compared to Session #4. This is caused by storing the slices in a balanced climate between Session #3 and #4 which caused remarkable visual changes. As expected, the lowest CS-Code distances are computed between Session 1–2 and 2–3.

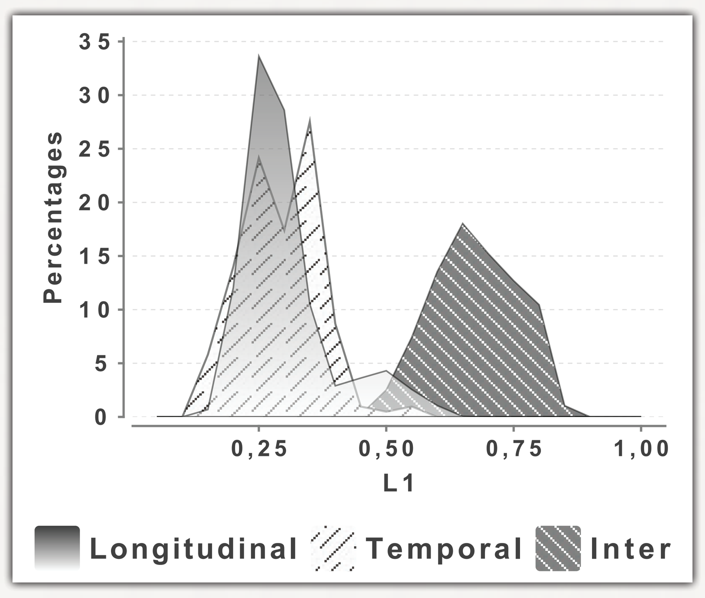

Figure 4. L_1 norm matching SDs

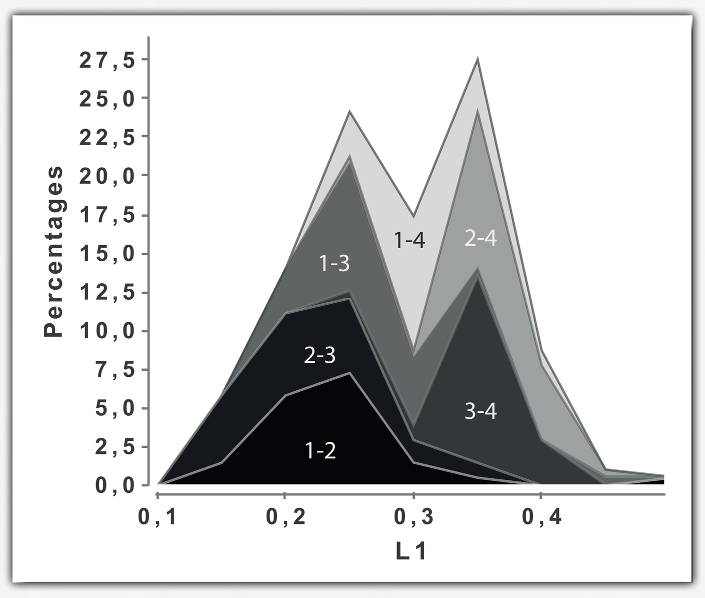

Figure 5. Temporal SD - stacked session subsets

Longitudinal Variances:

The chart in Fig. 6 illustrates the mean matching scores (L_1 norm) for different slice distances grouped session-wise. For each session the mean CS-Code distances increase with an increasing slice distance.

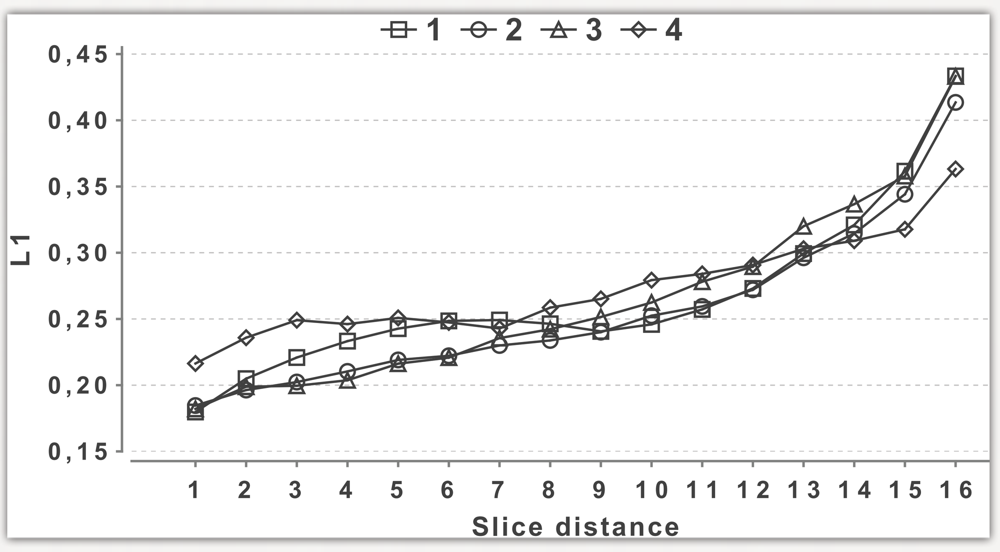

Figure 6. Longitudinal variances - matching score analysis

For further informations please visit *http://www.wavelab.at/project-treebio.shtml* **or contact** rschraml@cosy.sbg.ac.at
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