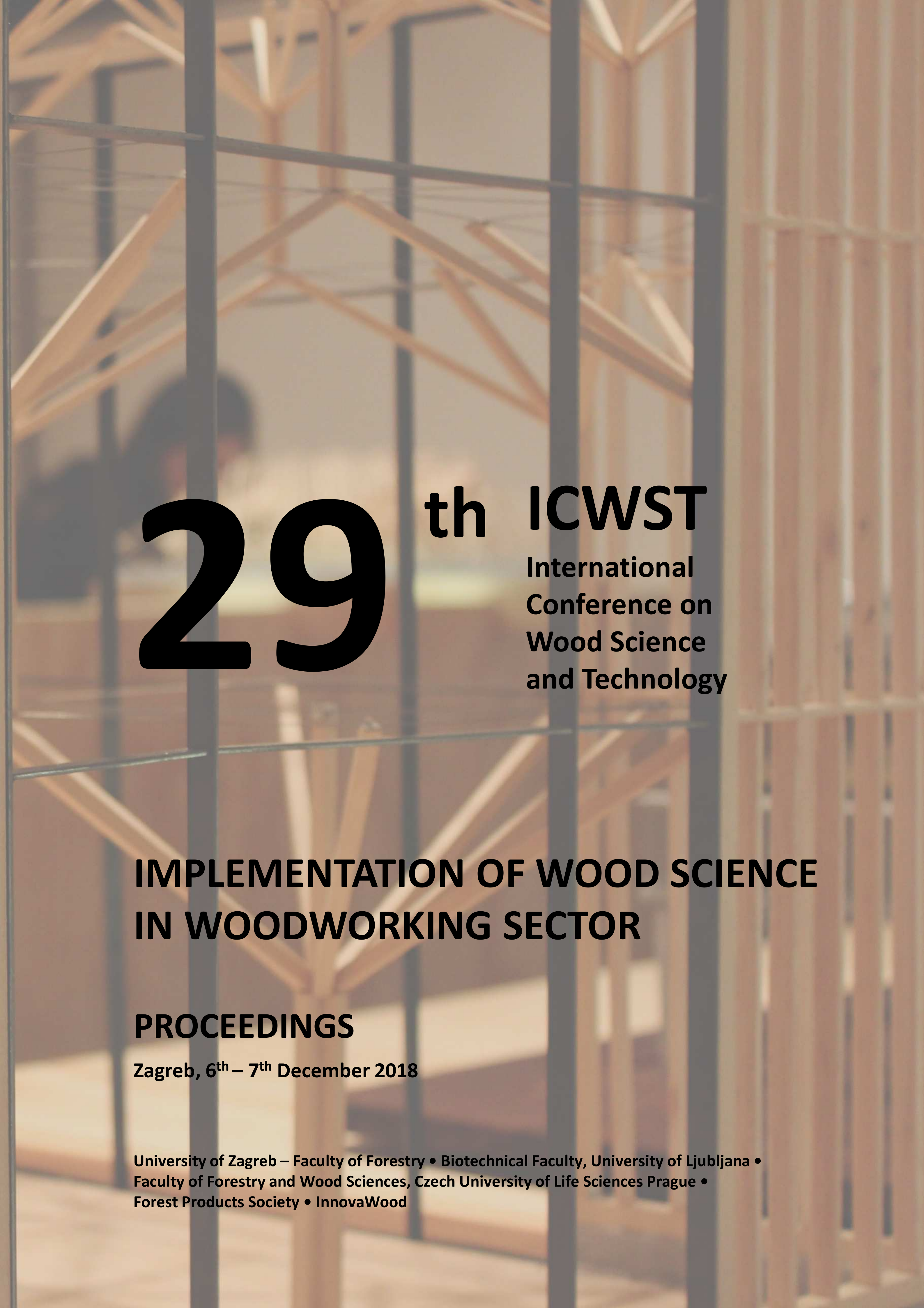

29th ICWST

International Conference on Wood Science and Technology

IMPLEMENTATION OF WOOD SCIENCE IN WOODWORKING SECTOR

PROCEEDINGS

Zagreb, 6th – 7th December 2018

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FOREWORD

Continuous changes on international market open up new horizons and opportunities, and the new strategies adopted by Europe and the world bring new concepts that need to be adapted and followed. This concept seeks increased social cohesion, striking with the harmful effects of climate change, nature preservation and the creation of a healthy environment. At the same time, creative potentials are open to new knowledge and innovative processes whose primary objective is to adapt to the needs of customers and the environment.

One of the activities carried out in recent years in order to preserve and stimulate rational utilization of raw material is certainly the traditional international scientific conference AMBIENTA. During its continuous sequence in the last 28 years it has become a platform for meeting and networking among scientists, teachers, researchers, students and professionals.

This year's conference, the third held under the title "*The implementation of science in the woodworking sector*" aims to ensure a multidisciplinary forum where all the participants have the opportunity to present and discuss innovations, trends and practical challenges they have faced in the world of wood science and technology, but also in relation to other materials, technologies, design and other related topics whose aim is to upgrade the wood industry.

We hope that this year's conference will contribute to awareness raising about the significance of wood as an irreplaceable natural raw material, and that the application of scientific research has a positive impact on the wood sector as well as any user of wood.

Assoc. Prof. Ivica Župčić, PhD

CONTENTS

LiDAR Technology and Linear Dynamical Systems for Classification of Tropical Tree Species

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ABSTRACT

To protect the value and potential of wood and forests, forest commissions, environmental agencies and scientists are focused on innovative solutions for environmental monitoring and management. To this end, a framework for tree classification that can contribute in the monitoring of wood resources, timber management and environmental protection is proposed in this paper. More specifically, we use LiDAR sensing technology and extract the skeleton of trees using the Fast Marching method. Then, we model them using linear dynamical systems taking advantage of the fact that each one of the tree species has been grown in a specific way and exhibits specific properties in the growing direction of it. This is achieved by dividing the tree skeletons into overlapping segments in the direction of z axes and creating higher-order patches consisting of trees' skeleton branching coordinates of each segment. Finally, due to the fact that the structure of tropical trees is complex, classification is performed introducing descriptors that take into account the combination of dynamic, appearance and noise parameters. For the evaluation of the proposed system, a dataset consisting of fifteen point clouds of common Caatinga tropical trees was created. Experimental results presented in this paper show the great application of the proposed methodology.

Key words: LiDAR remote sensing; linear dynamical systems; multichannel signal processing; pattern recognition; species classification; wood resources monitoring.

1. INTRODUCTION

The major wood products of tropical regions are associated with energy production through fuelwoods and with the production of numerous wood elements to be used for construction materials. Simultaneously, the non-wood products and services are associated with fodder, honey, fruits and medicines (Dore and Guevara, 2000). Nowadays, more and more finished wood products are being imported from tropical countries and tropical woods are used for the construction of luxury products. However, as the identification of tree species comprises the initial step of wood processing, the existence of difficulties in recognising tropical tree species and the resulting thoughtless cutting of them degrades the quality of life and ecosystem. Moreover, the difficulty in their recognition is intensified by the fact that the great variety of trees' characteristics and forests' heterogeneity affects the diversity of their colour, texture and thus aesthetic properties making the detection of tree species a difficult task (Silva, et al., 2018). It is worth mentioning that at least 50% of all species are found only in tropical forests (Lin, et al., 2016). To this end, the classification of tropical tree species is an essential step that plays a crucial role for forest and wood resources monitoring, timber management and environmental protection for the maintenance of ecosystem services that underlie human wellbeing.

As have been described by Szenjner and Emanuelli (2016), there are a lot of requirements for the identification of tropical tree species and many years of experience in the tropical forests field are required. However, based on the recent advances in the area of three-dimensional analysis, computer vision and pattern recognition, researchers have used 3D laser scanning technology in order to extract accurate information about the structure of large objects like buildings and trees that they examine. Light detection and ranging (LiDAR) sensors have been proved to be a powerful tool with a variety of capabilities (Kankare, et al., 2013) for the analysis of trees' structure and properties. LiDAR technologies generally are integrated into three categories: a) airborne (ALS), b) terrestrial (TLS) and c) mobile (MLS), laser scanning systems. In all aforementioned categories automatic solutions are required for the effective process of the data (Favorskaya and Jain, 2017).

Several methods currently exist for extracting 3D point clouds and geometric characteristics, as well as performing shape-based analysis for objects' recognition and modelling in urban environments (Bournez, et al., 2017, Golovinskiy, et al., 2009, Wang, et al., 2018). Some of these characteristics, as described by Bournez et al. (2017), that distinguish tree species, are tree and trunk height, crown shape and volume and branch density and diameter. Furthermore, Wang et al. (2008) used a LIDAR point cloud and developed a method for vertical canopy analysis and estimation of 3D models of trees in a forest. On the other hand, Sirmacek and Lindenbergh (2015), used a probability matrix and the point density for classifying point clouds into 'tree' and 'non-tree' categories. The main limitation, however, of all the above approaches for tropical trees classification is the fact that they do not take account of the extreme diversity that appears in geometric characteristics of them. However, it is considered that laser scanning captures much more object details than photogrammetry, which is very important for the complex tropical trees structure (Grussenmeyer, et al., 2008). Recently, Zou et al. (2017), proposed a voxel-based deep learning method to classify 1,340 tree samples using 3D point clouds.

In this paper, inspired by the multidimensional texture analysis approach for wood species recognition using macroscopic images (Barmpoutis, 2017, Barmpoutis, et al., 2018), we propose a new 3D analysis methodology using terrestrial laser scanning for the structural analysis of tropical trees and finally for the identification of their species for controlling, urban planning and management of SDTF areas. More specifically, this paper makes the following contributions:

- We propose a novel methodology for the classification of 3D point clouds and specifically of tree species. The corresponding extracted skeletons of trees are described by a linear dynamical system under the assumption that each tree is developed under a growing pattern that exhibit certain properties in the growing direction of it. Through analysing the trees' structure and dividing it into segments we create 3D patches consisting of trees' skeleton branching coordinates. Furthermore, due to the fact that the structure of tropical trees is complex, classification is performed by proposing new descriptors that bypass the limitations that were described above and take into account the combination of dynamic, appearance and noise parameters.
- To evaluate the efficiency of the proposed methodology, we created a dataset that consists of fifteen 3D point clouds of Caatinga tropical tree species. The experimental results show that the proposed methodology outperforms approaches that use geometric characteristics for 3D point clouds tree identification.

2. METHODOLOGY

The overall structure of the proposed methodology is shown in *Figure 1*. In the proposed methodology, a 3D laser scanner is used to capture the point clouds of isolated trees. Even though it is clear that the increase of the point clouds density improves the classification results, more data points require further computation, time and memory for the tree skeletons' reconstruction. To this end, the next step is the resampling of the 3D point clouds into local voxel spaces. To identify tree skeletons, we used the Fast Marching Method. Subsequently, to enable the representation of 3D skeleton points into the linear system model, we divided the skeleton tree volume into overlapping equal-sized segments as shown in *Figure 2*. In the next step each segment is described by two different descriptors for two different patch formations that take into account the relationship of appearance, dynamics and noise covariance of tree skeletons. Four histogram representations are calculated in total for the structure of each tree, based on the above descriptors. Finally, identification of the trees is performed by estimating the distances of concatenated histograms between different species.

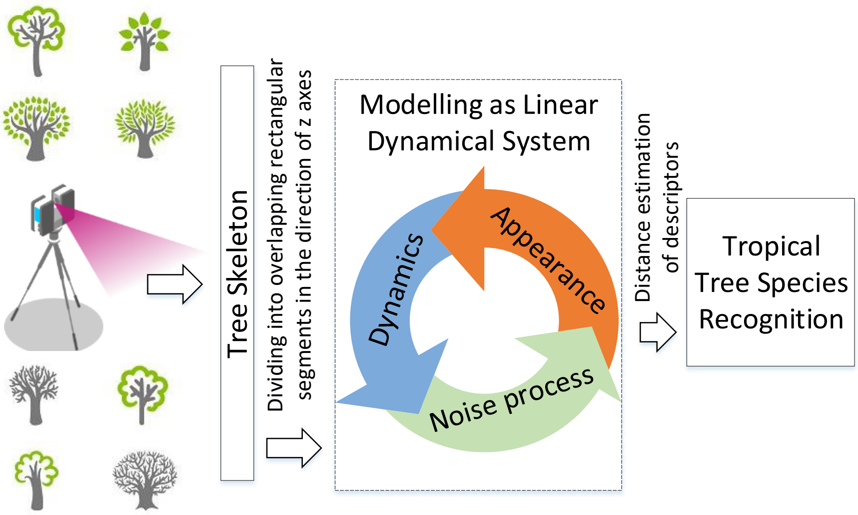
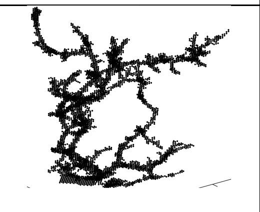
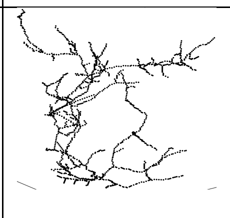
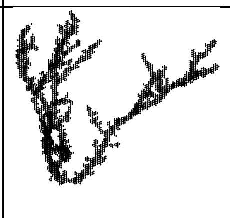
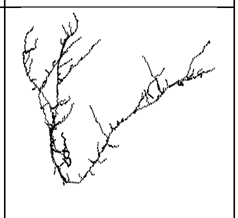
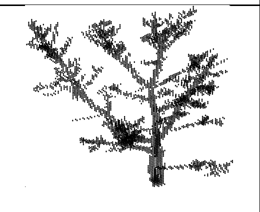
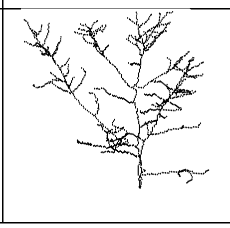
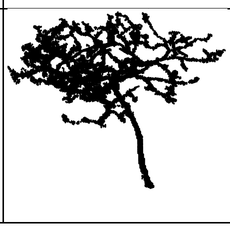
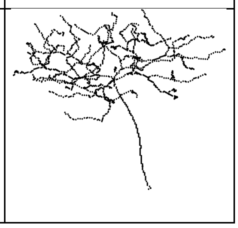


Figure 1. The proposed methodology for Tree Species Classification

2.1. Skeletons extraction of Caatinga trees

The extraction of tree skeletons is a significant step for the representation, path planning, visualization, structure analysis and classification of trees' data. In most studies, estimating skeletons or skeletonization of 3D point clouds has been achieved in four different ways: a) removing the boundary of a 3d point cloud layer by layer, known as morphological thinning (Zhou and Toga, 1999), b) computing Voronoi diagrams of discrete polylines like boundaries known as geometric and topological structure methods (Ying, et al., 2015), c) computing distance transform (DT) of the object's boundary (Hassouna and Farag, 2007, Van Uiter and Bitter, 2007) and d) generating quantitative structure models (QSMs) (Raumonen, et al., 2015). In our methodology, we used a distance transform method and specifically, we introduced the Fast Marching Method (FMM) for tree skeletonization.

Table 1. Skeletonization of trees applying FMM

	3D point cloud	FMM		3D point cloud	FMM
Commiphora leptophloeos			**Cnidoscolus quercifolius**		
Sapium glandulosum			**Manihot pseudoglaziovii**		

The FMM is the most representative distance transform method and it is applied to binary images with skeletonization usages basically for medical purposes (Van Uiter and Bitter, 2007). For the tree skeletonization, an FMM approach was used and applied to voxel space binary images of trees (*Table 1*). This approach takes into account level sets with a positive evolution speed, which is based on distance values, and represents the isosurface by solving the Eikonal equation:

$$|\nabla T|F = 1 \tag{1}$$

where T is the arrival time function and F is the speed of evolution function. The discretization of Eq. (1) is given by:

$$max\left(D_{i,j,k}^{-x}, 0\right)^2 + min\left(D_{i,j,k}^{+x}, 0\right)^2 + max\left(D_{i,j,k}^{-y}, 0\right)^2 + min\left(D_{i,j,k}^{+y}, 0\right)^2 + max\left(D_{i,j,k}^{-z}, 0\right)^2 + min\left(D_{i,j,k}^{+z}, 0\right)^2 = F_{i,j,k}^{-2} \tag{2}$$

where $D_{i,j,k}^{-x}$ and $D_{i,j,k}^{+x}$ are values resulting from standard backward and forward difference calculations at location (i, j, k).

2.2. Representations of Tropical trees through Linear Model Systems

In the case of forestry and species recognition applications, macroscopic wood images that contain periodic spatially-evolving characteristics have been considered to be a collection of multidimensional signals and have been modelled using linear dynamical model (Doretto, et al., 2003, Barmpoutis, 2017, Barmpoutis, et al., 2018). More specifically, they divided each image into horizontal patches, vertical patches and blocks and they adopted the following linear system, to extract appearance information and dynamics of patches.

$$x(t+1) = Ax(t) + Bv(t) \tag{3}$$
$$y(t) = \bar{y} + Cx(t) + q(t) \tag{4}$$

where $x(t)$ is the hidden state of the system, $y(t)$ is the observed data, $A \in \mathcal{R}^{n\times n}$ is the state transfer matrix, $B \in \mathcal{R}^{n\times n_v}$ is the process noise input matrix, $C \in \mathcal{R}^{m\times n}$ maps the hidden state to the output of the system, n is the order of the system and m is the number of data elements in each data.

For a given 3D point cloud of a tree, we consider its extracted skeleton to be described by a linear system under the assumption that each tree, especially tropical, is developed under a complex growing pattern that exhibits certain stationarity properties in the growing direction of it. Since the growing direction of a tree is in the z axes, we propose the structure division of a tree into N equally sized and overlapping segments. The size of each segment was defined equal to 3 (it consists of three 2D slides), as shown in *Figure 2*. For each segment we created two different structures (i.e., patch formations) $\boldsymbol{T}^{k\times G\times l}$ and $\boldsymbol{T}^{G\times k\times l}$ containing the corresponding G coordinates of it, where k are the x, y and z tree skeleton coordinates and l is the number of slides of each segment (in our experiments we set $l = 3$, *Figure 3*). For the purpose of describing and modelling the skeletons of trees, a numerous of tensors were created for each one of them. In the analysis of tensor taking into account the fact that the structure of trees, especially for tropical species, is complex and uncertain we consider the estimation of the noise covariance of the linear system model necessary. To this end, we adopt the transformation $Q = BB^\intercal$, which is used to incorporate the B matrix in noise covariance (Ravichandran, et al., 2013). Hence, we propose two different descriptors that take into account the relationship of appearance, dynamics and noise covariance of tree skeletons as follows. On the tensor of each segment we apply higher order singular value decomposition:

$$\boldsymbol{T} = S \times_1 U_{(1)} \times_2 U_{(2)} \times_3 U_{(3)} \tag{5}$$

where, $\boldsymbol{S} \in \mathcal{R}^{3\times G\times 3}$ is the core tensor, while $U_{(1)} \in \mathcal{R}^{3\times 3}$, $U_{(2)} \in \mathcal{R}^{G\times G}$ and $U_{(3)} \in \mathcal{R}^{3\times 3}$ are orthogonal matrices containing the orthonormal vectors spanning the column space of the matrix and the operator $\times_j$ denotes the j-mode product between a tensor and a matrix.

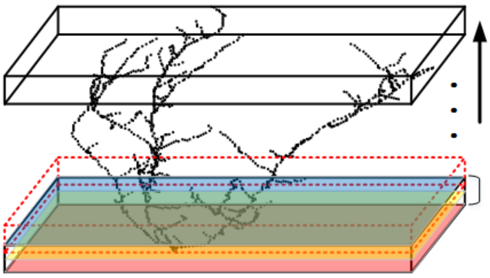


Figure 2. Dividing tree skeletons into N equally sized overlapping 3D segments in the direction of axes z. It is shown that each segment consists of three slides

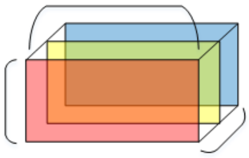


Figure 3. The structure of 3D patches consisting of trees' skeleton branching coordinates for each segment

After the identification of A and C system parameters of the linear dynamical model (Ravichandran, et al., 2013) the estimation of Q is performed using the states of the system Z as follows:

$$Q = \frac{1}{N-1}\sum_{t=1}^{F-1} v_t'(v_t^i)^{\top} \tag{6}$$

where, $v_t' = Bv(t) = z(t+1) - Az(t)$.

Finally, based on remarks about process noise covariance of Wang et al. (2017), we consider that the noise covariance matrix might be used in combination with dynamics as new descriptors. Hence, each segment of the tree skeleton can be represented by two different descriptors and they can be applied to generate system state estimation based on the state transfer matrix, observation matrix and covariance matrix Q. The proposed LDS descriptors are created by the pairs of matrices $M_1 = (A, C)$ and $M_2 = (A, Q)$. Similarly, to Barmpoutis et al. (2018), two codebooks of 96 codewords are formed from the different kind of extracted LDS descriptors using a k-medoid clustering algorithm. Thus, each LDS that represents a segment corresponds to a histogram bin. Each 3D skeleton point cloud is then represented as a term frequency histogram. Then, to exploit the complementary information of the descriptors we concatenate the extracted histograms.

In order to classify each tree in the appropriate category of tree species, we estimated the distances between concatenated histogram of each tree. Considering the shuffle invariance of the estimated nominal histograms, we used Euclidean distance as a similarity metric of different tree samples:

$$d(H_1, H_2) = \sqrt{(h_{11} - h_{21})^2 + \cdots + (h_{1n} - h_{2n})^2} \quad (7)$$

Finally, each tree is classified in the category of the tree that the similarity metric is minimum. The advantage of this model is that it takes into account the combination of the appearance of segments of tree skeleton which is modelled by C matrices, the dynamics that are represented by A and the noise covariance matrix that is estimated by Q.

3. EXPERIMENTAL RESULTS

In this section, we present the experimental evaluation of our methodology using the fifteen 3D point clouds of isolated Caatinga tree species. Eight of them were scanned inside and seven of them were scanned outside. The dataset consists of four common Caatinga tree species: *Commiphora leptophloeos*, *Cnidoscolus quercifolius*, *Sapium glandulosum* and *Manihot carthagenensis*. In order to overcome the variability problem of different scanning distances of trees as well as of heights of trees, all scanning trees were converted into similar scale. The experiments were performed with a PC that has an E5 2.4 GHz processor and 32 GB memory ram. To guarantee that the experimental results are generalized for making predictions regarding new data, the dataset was randomly partitioned into training and independent testing sets via a five-fold cross validation. Thus, each of the five subsets was used as a holdout testing dataset as the model was trained with the rest of four subsets.

To evaluate the performance of the proposed method, experimental results were obtained for the two different descriptors. In addition, to explain how the different descriptors contribute in classification rates, we performed the experiments using different patch formations as shown in *Table 2*. The proposed algorithm achieves true classification rate of 80% using different formations of data and M_1 and M_2 descriptors. Furthermore, experimental results make evident that the individual feature representations contain complementary information and therefore the detection accuracy after fusion of the four descriptors is increased to 86.6%.

Table 2. Skeletonization of trees applying FMM

Patch Formation		$M_1 = (A, C)$	$M_2 = (A, Q)$	*Fusion*
$\boldsymbol{xyz \times G \times 3}$	FMM	80%	73.3%	86.6%
$\boldsymbol{yxz \times G \times 3}$	FMM	66.7%	80%	

Furthermore, we evaluated the performance of the proposed methodology against approaches that use combination of geometry measurements (*Table 3*). Firstly, we compared it with a geometric approach that uses tree structure characteristics, namely tree and trunk height, crown shape and volume and branch density and diameter (Bournez, et al., 2017). The recognition rate using the above measurements and an SVM classifier is 66.6%. Furthermore, noticing that 3D Voronoi diagrams (VD) and Delaunay Triangulations (DT) are able and have been used to describe and quantify 3D objects defining spatial pattern and relationships between the selected 3D points (Ying, et al., 2015), we compared the proposed method with a set of features that are based on perimeters and areas of Voronoi Diagrams and Delaunay Triangulations of the given sets of critical points of trees. For our experiments we used node and end branch points and the positive detection rate found 53.3% and 60% for use of VD and DT respectively. Obviously, the results of the proposed method outperform urban objects and trees recognition approaches that use geometric characteristics, as were described in the previous sections.

Table 3. Comparison results of tree species recognition

	Detection rate
Proposed	86.6%
Voronoi diagrams	53.3%
Delaunay Triangulations	60%
Geometric approach	66.6%

4. CONCLUSIONS

In this paper we presented a novel approach for tropical tree species recognition using 3D point clouds through skeleton extraction and analysis using linear dynamical systems with the potential to significantly contribute to forest and wood resources monitoring, timber management and environmental protection. Initially, tree skeletons were extracted and by the assumption that each tropical tree is developed under a complex growing pattern, we divided tree structures into segments. For each segment we extracted two different descriptors that take into account dynamics, appearance and noise parameters. The proposed algorithm derived the estimation of noise covariance matrix and created new descriptors. The results showed that the dynamics, appearance and noise covariance matrix might be used as new descriptors for 3D point clouds tree classification. Finally, in the future, we aim to extend our database using more tree species that exist in various regions. Furthermore, we aim to use the proposed methodology in order to assist foresters in determination of the selection of trees that should be cut down, depending on when they reach their economically 'mature' stages.

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