Objective Evaluation of 3D Reconstructed Plants and Trees from 2D Image Data

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Abstract—When several approaches on image-based modeling of 3D plants/trees were successfully developed, they usually applied a subjective inspection to assess the quality of synthesized plants/trees based on their given image data. For this reason, we propose a preliminary study on objective approaches in evaluating the synthesized plants from the given image data. Two measures, in a general name of “Resemblance Index (RI)”, are defined and investigated based on the normalized mutual information (RI_{MI}), and coincident-bit-counting criterion (RI_{CBC}), respectively. We propose a strategy of hierarchical evaluations on different attributes of objects. In this study, we apply the proposed approach in evaluations of 3D plants but only consider the geometrical and crown distribution attributes. The numerical investigations confirm the approach to be useful for a fast evaluation of 3D reconstructed plants/trees from image data. Discussions are given about the two measures based on the numerical examples.

Index Terms—Image-based modeling, 3D plant, objective measure, mutual information, resemblance, similarity

I. INTRODUCTION

A study of 3D plants reconstructed from the real data of the target plants has received increasing attentions in recent years [14, 18-19, 21-22, 25, 28-29]. The driving force for this study is coming from two sources of applications. The first one is to develop a fast measurement technique of plant structures and geometries in applications of forestry and agriculture. The second one is to demonstrate a virtual world with a high degree of resemblance to the real world, which is increasingly demanded in several application backgrounds, such as virtual reality, digital games, or advertisements. Basically, there exist two up-to-date techniques in acquisitions of the original data for reconstructing 3D plants, i.e., laser range scanner [4, 28-29] and camera [14, 18-19]. The first instrument is more accurate for measuring the geometric properties of objects, but it is usually more expensive than a common camera. Moreover, this technique also needs a camera for obtaining the texture information about the objects if a realistic rendering is required. The multiple-view image data from a camera technique present several advantages over the approach using a laser scanning technique. The most significant advantage is that image data can provide an overall measure on evaluating 3D plants with respect to multiple attributes of the target plants, which will be described in next section.

While several approaches on image-based modeling of 3D plants/trees were successfully developed, however, most results from those 3D plants were evaluated based on human visual inspections by comparing the synthesized plants with their image data on the original targets. In principle, this is a subjective evaluation, which cannot give a quantitative measure to the synthesized accuracy from the image data.

In this work, we will focus our study on uses of 2D image data for evaluating the synthesized quality of 3D plants. Since plants present one of the most complex objects in this world, up to now there seems still missing an objective, yet simple, approach in evaluations of the synthesized quality of 3D plants from image data. In fact, it is still an open problem of assessing the representation quality of complex objects in the “virtual world” from image data of its “real world”. Therefore, this work attempts to propose an objective evaluation approach on 3D plants. For simplifying the study, we only consider the geometrical and crown distribution attributes of simple trees. The present correspondence is organized as follows. In Section II, an objective evaluation approach is proposed for 3D object models through 2D image data. Some related work is given in Section III. Two resemblance indexes (or RIs) are defined based on the normalized mutual information and a coincident-bit-counting criterion in Section IV. A strategy of hierarchical evaluations on different attributes of objects is proposed in together with the procedures for the proposed approach in Section V. The numerical examples are conducted in Section VI to demonstrate the effectiveness of the approach. Moreover, discussions about the two measures of RIs are given from the numerical results. Finally, we summarize the contributions and future work in Section VII.

II. IMAGE-BASED EVALUATION APPROACH

In this section, we will propose an objective evaluation approach on 3D virtual objects based on 2D image data sets. Fig. 1 shows a schematic diagram of the proposed approach. Two data sets are defined.

Definition 1. Target Data Set (T) and Virtual Data Set (V). A target data set represents image data of target objects on which one intends to model. This data set is denoted by \( T = (T_1, T_2, ..., T_k) \), with \( k \) number of images taken from different temporal/spatial viewpoints on the target objects. A virtual data set is the image data of virtual objects which are the output from “3D Model and Rendering” in Fig. 1. It is denoted by \( V = (V_1, V_2, ..., V_k) \). Therefore, T and V form K sets of image pairs. Two assumptions are made respectively for the two data sets.

Assumption 1. On target data set T. Data set T is considered as a baseline, or a reference, for evaluations, which implies the data are noise free, and representing exactly the projection images of the target objects.
be too rigorous for achieving in applications. If the assumptions are not satisfied, a modular on image process will be needed. For example, when no “pixel-to-pixel” correspondences exit between two images, an image registration scheme can be used, but the final RI value may include error components from a misregistration. In principle, the two assumptions can be partially relaxed depending on the cases concerned. Second, an evaluation from 2D images for 3D objects provides, in principle, an approximation approach. We adopt the term of “resemblance”, rather than “similarity”, for the following reasons. Firstly, the conventional definition of similarity with respect to a geometrical attribute will preserve the property for “ratios of distances” [9]. This property means that, if one object is transformed by a scaling operation for a new object, they are considered to be the same in the similarity measure. For modeling 3D plants/trees, this is not a desirable property. Secondly, this approach is approximately to estimate the differences of 3D objects from 2D images. When RI=1, we cannot conclude that the 3D objects are exactly the same. In this situation, they are exactly resemble only in their visual appearances. Finally, for a complex tree, one is most likely to miss much information in measuring 3D resemblance from 2D image data comparisons.

III. RELATED WORK

In literature, to our knowledge, it seems no open publication available in studying the evaluation of reconstructed 3D plants/trees from 2D image data. However, there exist significant investigations on similarity subject from application backgrounds of image registration [2] and image retrieval [23]. Since there exist numerous measures of similarity in uses, we will only present some of them so that one can have a better view for selections of proper measures.

One of the pioneer works on similarity study in image registration is “Sequential Similarity Detection Algorithm (SSDA)” developed by Barnea and Silverman [1] in 1972. The other most conventional measures of similarity in the same context [2] are “Mean Square Difference (MSD)” and “Normalized Cross Correlation (NCC)”. However, a misregistration often occurs when using these measures if significant differences exist between two images. The main reason is that the measures calculate the differences of pixel values which is very sensitive to noise [3]. In 1993, Chiang and Sullivan [5] proposed “Coincident Bit Counting (CBC)” as a similarity measure for studying image registration, which is to obtain the number of matching pixels between two images. This measure, irrespective of pixel values in some extent, presented a better performance than the conventional measures. In 1995, two research groups independently proposed the uses of mutual information (MI) for image registration criteria [13, 26]. The principle of MI is to measure the statistical dependence between two random variables or the amount of information that one variable contains about the other. In the context of image registration, an MI criterion requires to be maximal between the image intensity values of corresponding voxel/pixel pairs on which the images are considered to be geometrically aligned. In 1997, Maes et al. [13] proposed a generalized framework of mutual information on the study of multimodality medical image registration. They proved that the previous methods, using 2D joint histogram of the image intensities of the corresponding voxel/pixel pairs, can fall into the framework of information-based criteria. Other improved approaches were reported on MI measures, such as using Renyi entropy [16], normalized MI [24], and gradient-included MI [15]. It seems that MI has become to be a main similarity criterion used in the study of image registration [6, 11,
Several investigations have been reported for comparing MI measure with other similarity measures. Cole-Rhodes, et al [6] studied two measures on correlation coefficient (CC) and MI. Freire et al [11] conducted a comparative study on similarity measures such as MI, MSD, correlation ratio (CR), Geman-McClure (GM) error norms and etc. Numerical studies showed that GM was the best measure. Zhu and Cochoff [32] proposed the normalized logarithmic likelihood (NLL) in their studies and observed that NLL measure obtained a comparable performance with MI one.

In studies on image retrieval, Smelnders, et al, [23] reviewed the similarity approaches for retrieval sorted by color, texture, and local geometry. Several schemes have been reported in applications. These include similarity between features, similarity of object silhouettes, similarity of salient feature, similarity of structure feature, and similarity at the semantic level. Several definitions of distance are used in calculating similarity, such as a simple Euclidean distance, Minkowski distance for color histogram, Hausdorff metric for shape description, etc.

IV. FORMULAS

In this section, we will present the formulas in calculation of resemblance index for assessing 3D models of trees quantitatively from image data. As a preliminary study, two principles will be adopted for evaluation measures as RI, that is, information-based and coincident-bit-counting criteria. In the first principle, given a pair of gray intensity images $T(x,y)$ and $V(x,y)$, their Shannon-type mutual information of images is defined as

$$ I(T,V) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{TV}(i,j) \log \frac{p_{TV}(i,j)}{p_T(i)p_V(j)} $$

where $p_{TV}(i,j)$ is the joint probability; $p_T(i)$ and $p_V(j)$ are the marginal probabilities of individual values occurring for each image; and $L$ is the total number of gray levels. In this work, we use the normalization histogram method for estimations of the probability distributions [13], such as:

$$ p_{TV}(i,j) = \frac{h_{TV}(i,j)}{\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} h_{TV}(i,j)} $$

where $h_{TV}(i,j)$ is the joint histogram for representing the number of corresponding pairs having intensity value $i$ in $T$ and intensity value $j$ in $V$. The marginal probability density functions (PDFs) of two images are:

$$ p_T(i) = \sum_{j=0}^{L-1} p_{TV}(i,j) $$

$$ p_V(j) = \sum_{i=0}^{L-1} p_{TV}(i,j) $$

From the marginal PDFs defined above, one is able to calculate their entropies $H(T)$ and $H(V)$ directly [8].

**Definition 3:** Information-based $RI$ ($RI_{inf}$). The normalized mutual information used by [13] is adopted as the first definition of $RI$:

$$ RI_{inf}(T,V) = 2 \cdot \frac{I(T,V)}{H(T)+H(V)} $$

As a relative entropy, the information-based $RI$ presents in principle a specific score of correlations [8] between images in a spatial means. Obviously, this index satisfies both symmetric and normalization properties. The monotonicity property will be discussed later.

**Definition 4:** Coincident-Bit-Counting-based $RI$ ($RI_{cbc}$). This measure is based on the idea of the coincident bit counting [5] as the second definition of $RI$:

$$ RI_{cbc}(T,V) = \frac{N_{cbc}(T,V)}{N_{BC}(T,V)} $$

where $N_{cbc}$ is the coincident bit counting number from the joint histogram between images $T$ and $V$, and $N_{BC}$ is the total bit counting number in the joint histogram. They are defined respectively as:

$$ N_{cbc}(T,V) = \sum_{i=0}^{L-1} h_{TV}(i,j) $$

$$ N_{BC}(T,V) = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} h_{TV}(i,j) $$

In principle, $RI_{cbc}$ works like an accuracy-based measure for a classification problem. The joint histogram $h_{TV}$ can be considered as a confusion matrix [12]. The diagonal terms represent the exact classification numbers, and non-diagonal terms are misclassification numbers. $RI_{cbc}$ measure satisfies both symmetric and normalization properties.

However, both definitions described in eqs. (5) and (6), originally from the studies on image registration, will not be exactly proper in use for the present study. Therefore, for applying the measures properly, some definitions and intuitions are given below.

**Definition 5:** Target Pixel Subset ($TP$) and Background Pixel Subset ($BP$). For image data set $T$ (or $V$), it contains two groups of pixels which form two data subsets. The pixels representing target objects are within target pixel subset ($TP$). The pixels outside of $TP$ are considered belonging to background pixel subset ($BP$). We denote $TP_T$ and $TP_V$ as two subsets within $T$. Therefore, one can have relations as, $TP_T \subseteq T$, $BP_T \subseteq T$, $TP_T \cap BP_T = \emptyset$ and $TP_V \cap BP_V = \emptyset$, where $\emptyset$ is an empty set. The relations also hold for image data set $V$.

**Definition 6:** Intersection Background Pixel Subsets ($IB$). The intersection background pixel subsets ($IB$) represent all pixels from an intersection operation on the background pixel subsets $BP$ from both data sets $T$ and $V$ respectively in forms of:

$$ TP_T = T \cap TP_V $$

$$ TP_V = V \cap TP_T $$

**Definition 7:** Union Target Pixel Subsets ($UT$). The union target pixel subsets ($UT$) represent all pixels from an union operation on the target pixel subsets $TP$ from both data sets $T$ and $V$ respectively in forms of:

$$ TP_T = T \cup TP_V $$

**Definition 8:** Intersection Background Pixel Subsets ($IB$). The intersection background pixel subsets ($IB$) represent all pixels from a intersection operation on the background pixel subsets $BP$ from both data sets $T$ and $V$ respectively in forms of:

$$ TP_T = T \cap TP_V $$

$$ TP_V = V \cap TP_T $$

The two subsets $TP_T$ and $V_T$ have the same data sizes and share the same pixel coordinates. One can have the relations as $TP_T \cup TP_V = T$ and $TP_T \cap TP_V = \emptyset$; and the same for $V_T$, $V_V$, and $V$.

From Intuitions 2, we can see that the proper definitions of $RI$ measures should be calculated from data subsets of $TP_T$ and $V_T$ by:

$$ RI_{inf}(TP_T,V_T) = \frac{I(T_P,V_T)}{H(T_P)+H(V_T)} $$

$$ RI_{cbc}(TP_T,V_T) = \frac{N_{cbc}(TP_T,V_T)}{N_{BC}(TP_T,V_T)} $$

rather than from $T$ and $V$ directly. Then, $RI$ measures will be independent to the background pixels from $IB$ data. Only those background pixels misclassified as the target pixels will be
accounted in the calculations. Therefore, both measures in eq. (11) and (12) will present suitable indexes to evaluate a resemblance of target objects and virtual objects.

The formulas given above are based on one pair of grey images. If multiple pairs of RGB/HSL image data are used for evaluations, an overall RI can be obtained from a simple mean calculation:

\[
RI_{\text{overall}} = \frac{1}{3K} \sum_{i=1}^{K} \sum_{j=i}^{3K} RI_i^j
\]

V. STRATEGY AND PROCEDURES

For complex objects like plants or trees, resemblance evaluations can be processed hierarchically with respect to different attributes of the targets. This strategy is proposed for the reason to simplify 3D modeling and evaluation of plants/trees. Table I lists three levels for such evaluations. The first level is to examine a target on the attributes of its geometries and structures. They are the most primary attributes for 3D objects like trees. In this level, we suggest to apply binary image data since they are sufficient in most cases to represent the geometric and structural attributes of the targets. For example, if the trunks and branches are the concern in 3D modeling, evaluations based on binary image data will be appropriate and efficient, which are significantly faster than using grey-level images or RGB images directly.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>PROPOSED HIERARCHICAL EVALUATIONS WITH RESPECT TO ATTRIBUTES OF VIRTUAL PLANT/TREE OBJECTS AND RELATED IMAGE DATA TYPES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hierarchical</td>
<td>Attributes of Plants/Trees</td>
</tr>
<tr>
<td>Evaluations</td>
<td>Geometries and Structures</td>
</tr>
<tr>
<td>Levels</td>
<td>Crown Distributions</td>
</tr>
<tr>
<td>Level 3</td>
<td>Light Effect, etc.</td>
</tr>
</tbody>
</table>

A use of grey-level image data is suggested for examining crown distributions as the second level evaluation. From a visual appearance, crown distributions can be defined as spatial intensity information formed from leafy branches. This is also an important attribute concerned in 3D modeling on a leaf-crowned tree or a plantation with numerous trees. In these situations, we consider that grey-level images will be sufficient in representing such spatial intensity information. If more attributes are required for evaluations, such as the texture, light effects, etc., RGB/HSL images are necessary in use.

For simplifying evaluations, we suggest to apply the proposed strategy level by level. However, it should be recognized that the strategy of hierarchical evaluations is proposed under an assumption that no coupling effects exist among investigated attributes. If the effects cannot be neglected, RGB/HSL image data may be necessary for an evaluation on overall attributes, which is generally more difficult and expensive in processing.

The detailed procedures in implementation of evaluations of 3D plants/trees are given below:

I. Define the attribute(s) for the evaluation, and then prepare the suitable image data pair T and V accordingly;
II. Construct two subsets T_{UT} and V_{UT} from T and V, respectively;
III. Form the joint histogram matrix from T_{UT} and V_{UT}, which defined as h_{UT}(i,j);
IV. Calculate RI_{UT} and RI_{CBC} from h_{UT}(i,j) when using eq. (11) and (12), respectively;
V. Calculate RI_{Overall} if more than one pair of image data is used, or color space features are necessary for evaluations.

VI. NUMERICAL EXAMPLE

In this section, we will present numerical examples for evaluations on 3D trees in together with discussions about two measures proposed in this work.

A. Evaluation on a trunked tree

This example will evaluate a 3D trunked tree with respect to geometries and structures. Therefore, only binary images are used in the evaluation. Fig. 2 shows a pair of images from a real tree RGB image and a virtual tree from a 3D model, respectively.

In this numerical test, we firstly transfer the original images into binary images. Two pairs of binary images are obtained. The first pair of the binary images is in the original sizes with 190×256 pixels, and the second one is made from the first pair of images, but adding 190×10 background pixels on the left sides of the images. From Intuition 2 we understand that both pairs of images should give the same RI values. The objective of using two pairs of images is to justify the definitions of our proposed RI measures in eqs. (11) and (12) by comparison with those measures which directly calculate the NMI or CBC criteria in eqs. (5) and (6).

![Fig. 2 Image data for evaluations of tree trunks: (a) Image of real tree, (b) image of virtual tree.](image)

Table II lists the results of RIs on two pairs of binary images. Some remarks can be obtained from the observations on the table:

Remark 1. The results of RIs using eqs. (5) and (6) show increasing values when background pixels are added. This phenomenon indicates the directly uses of NMI or CBC criteria on images as RI will be not appropriate in evaluations.

Remark 2. The results of RIs using eqs. (11) and (12) show the same for themselves respectively on the two pairs of images. Therefore, RIs defined from eq. (11) and (12) are proper regarding to Intuition 2.

Remark 3. Two RIs from eqs. (11) and (12) show different values for the present examples. Which one is more proper with respect to Intuition I needs to be investigated further.
B. Numerical investigations on similarity and RI’s

Viewing Remark 3 above, we can find out that two RIs defined from eqs. (11) and (12) satisfy the first two properties in Intuition 1, i.e., symmetry and normalization. Only one property, monotonicity, needs to be examined for two RIs. For investigating this property properly, we need to define similarity in accordance with our intuition.

Intuition 3: Similarity defined from the joint histogram matrix.

Since both RIs in eqs. (11) and (12) are calculated from joint histogram matrix \( h_{A,B} \), a similarity analysis can be conducted directly from a given joint histogram matrix. Intuitively, the necessary conditions for this analysis will be that the diagonal terms of \( h_{A,B} \) reflect the degree of similarity, and the off-diagonal terms reflect the degree of dissimilarity.

The similarity defined above is quite rough, but meaningful in uses. At least this intuition can be considered as a bottom line for a similarity analysis. In other words, if this intuition cannot be satisfied, a similarity relation will be broken. As a preliminary study, we propose this intuition for the reason of simplicity. Therefore, one is able to apply synthesized, yet simple, data sets for study, we propose this intuition for the reason of simplicity.

<table>
<thead>
<tr>
<th>Binary Images (190x256)</th>
<th>Binary Images + Background Pixels (190x10)</th>
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</thead>
<tbody>
<tr>
<td>( RI_{h} ) using eq. (5)</td>
<td>0.208</td>
</tr>
<tr>
<td>( RI_{c} ) using eq. (6)</td>
<td>0.877</td>
</tr>
<tr>
<td>( RI_{s} ) using eq. (11)</td>
<td>0.234</td>
</tr>
<tr>
<td>( RI_{sc} ) using eq. (12)</td>
<td>0.379</td>
</tr>
</tbody>
</table>

\[ h_{A,B} = \begin{bmatrix} 0& 30 & 0 & 0 \\ 64 & 44 & 0 & 0 \\ 0 & 0 & 57 & 38 \\ 0 & 0 & 3 & 2 \end{bmatrix} \tag{14} \]

and

\[ h_{A,C} = \begin{bmatrix} 0& 30 & 0 & 0 \\ 64 & 44 & 0 & 0 \\ 0 & 0 & 27 & 68 \\ 0 & 0 & 3 & 2 \end{bmatrix} \tag{15} \]

where one can see that both matrices are 4 by 4 in size which indicates the number of intensity levels, \( L \), of the given images is 4. In this work, we always set \( h_{A,B}(0,0) = 0 \) for the reason this term corresponds to the bin of background pixels on both A and B images. Therefore, those background pixels outside the UT subsets will be not taken into account for RI calculations, as defined in eqs. (11) and (12). The two matrices do reflect that B is more resemble to A than C if viewing the differences on \( h_{A,C}(2,2) = 27 \) and \( h_{A,B}(2,2) = 27 \), but \( h_{A,B}(2,2) = 27 \) and \( h_{A,C}(2,2) = 38 \). The differences imply that B is improved over C by reducing the mismatching pixels on one off-diagonal term. According to Intuition 3, one relation holds on the given joint histogram matrices, that is, \( RI(A,B) > RI(A,C) \). However, this is not always true for \( RI_{s} \) defined in eq. (11). Table III lists the comparisons of RIs on the two joint histogram matrices. Two remarks can be achieved:

Remark 4. \( RI_{s} \) does not always satisfy Intuition 3, like the data points given by eqs. (14) and (15). The main reason is that mutual information does not present a monotonous property with respect to term variables of joint histogram matrices.

Remark 5. Examining eq. (12), we can see that \( RI_{sc} \) provides an exactly monotonous property with respect to the similarity defined from Intuition 3.

| Binary Images + Background Pixels (190x10) |
|-------------------------|------------------------------------------|
| \( RI_{h} \) using eq. (11) | 0.645 | 0.650 |
| \( RI_{c} \) using eq. (12) | 0.572 | 0.407 |

In fact, it is not straightforward to observe the phenomenons described by Remark 4 from eq. (11). In the work by Hu and Wang [12], we theoretically proved that mutual information defined in eq. (1) shows multiple valleys, or non-monotonocity, with respect to the term variables of joint histogram matrices. For example, the \( RI_{h} \) shows a local minimum for joint histogram matrices in a form of:

\[ h = \begin{bmatrix} \ldots & 0 & 0 & \ldots \\ \ldots & h_{ij} & 0 & \ldots \\ \ldots & 0 & h_{ij+1} & \ldots \\ \ldots & 0 & 0 & \ldots \end{bmatrix} \tag{16} \]

and with following relations:

\[ h_{ij} + h_{ij+1} = h_{ij+1} + h_{ij+1}, \text{ or,} \]

\[ h_{ij+1} + h_{ij+1} = h_{ij+1} + h_{ij+1} \tag{17} \]

Examining eq. (14), one can find the given matrix satisfies the conditions above. Numerical investigations also confirm the following relations when using \( RI_{s} \):

\[ RI_{s}(A,B) > RI_{s}(A,C) \rightarrow 'B' \text{ is more resemble to } A \text{ than } C' \tag{18} \]

\[ 'B' \text{ is more resemble to } A \text{ than } C' \text{ may not} \rightarrow RI_{s}(A,B) > RI_{s}(A,C) \tag{19} \]

where the symbol “→” stands for “leads to”. Therefore, we can reach the important remarks below on using mutual information as a similarity index, or \( RI_{s} \) in this work:

Remark 6. The Shannon-type mutual information has an intrinsic drawback as a similarity measure. While it can provide a property on globally increasing monotonicity with respect to similarity defined in Intuition 3, this measure may fail to present a proper evaluation in local regions because it exhibits local valleys as eqs. (16)-(17) with respect to the term variables of joint histogram matrices.

Remark 7. Eq. (18) indicates that the Shannon-type mutual information can be effective as an optimization function for similarity studies like image registrations, or 3D model refinement in Fig. 1.

Further comparing two measures, we can find their commons and differences as:

Remark 8. When an exactly similarity relation defined as Intuition 3 exists, \( RI_{sc} \) will produce the maximum results, such as

\[ RI_{sc}(A,B) = 1 \tag{20} \]

Remark 9. If an exactly similarity relation occurs, \( RI_{s} \) will show the following properties, such as

\[ RI_{s}(A,B) = \begin{cases} 1 & L \geq 2 \\ 0 & L = 2 \end{cases} \tag{21} \]

It means that \( RI_{s} \) suffers a drawback when using binary images. This drawback is come from that \( RI_{s} \) becomes to be degenerated for having only one class of pixels in calculations. Any entropy-
type measure, say, Shannon-, Renyi-entropy, or other divergences, will become inappropriate in this case (zero uncertainty for a single class).

**Remark 10.** When $\text{RI}_{\text{CBC}}=0$, it indicates that all diagonal terms of the joint histogram matrix will produce zero values:

$$h_{i,j}=0, \quad i=0,1,\ldots,L-1$$

which also implies a zero degree of similarity if defined in Intuition 3.

**Remark 11.** When $\text{RI}_{\text{NI}}=0$, one specific case for its corresponding matrix is [12]:

$$h=egin{bmatrix}
0 & h_{0,j} & 0 \\
0 & h_{1,j} & 0 \\
0 & \ldots & 0 \\
0 & h_{j-1,j} & 0 \\
0 & h_{j,j} & 0 \\
0 & h_{j+1,j} & 0 \\
\vdots & \vdots & \vdots \\
0 & h_{L-1,j} & 0 \\
0 & 0 & 0
\end{bmatrix}$$

where $j \geq 0$, $j = 0,1,\ldots,L-1$.

This matrix means that only one column has non-zero value terms, and all other terms in the matrix are zeros. In this case, one can find that $\text{RI}_{\text{NBC}}>0$.

From the investigations above, we will consider that $\text{RI}_{\text{CBC}}$ is a better measure than $\text{RI}_{\text{NI}}$. However, $\text{RI}_{\text{CBC}}$ also presents some limitations for similarity evaluations. For example, it does not take the error types for mismatching bits into account. $\text{RI}_{\text{CBC}}$ implies the same weight among the off-diagonal terms in its calculations. On contrary, $\text{RI}_{\text{NI}}$ is able to balance the error weights on the off-diagonal terms naturally [12]. Therefore, both $\text{RI}_{\text{CBC}}$ and $\text{RI}_{\text{NI}}$ need to be improved in future work.

**C. Evaluation on a simplified leafy tree**

In apart from modeling evaluations between real-world objects and virtual-world objects, another important perspective of development of an objective measure is from simplification on virtual objects. In the concern of this work, a simplified tree or plant will be required in evaluations from a quantitative, yet objective, measure. When a virtual tree is constructed, sometimes, a simplified tree is necessary for a real-time or an interactive rendering [20, 30-31]. Previous studies demonstrated that a vegetation rendering with million polygons does require simplified 3D trees for realizing an interactive feature. From viewpoint of the joint histogram matrix will produce zero values:

$$h_{i,j}=0, \quad i=0,1,\ldots,L-1$$

which also implies a zero degree of similarity if defined in Intuition 3.

From the investigations above, we will consider that $\text{RI}_{\text{CBC}}$ is a better measure than $\text{RI}_{\text{NI}}$. However, $\text{RI}_{\text{CBC}}$ also presents some limitations for similarity evaluations. For example, it does not take the error types for mismatching bits into account. $\text{RI}_{\text{CBC}}$ implies the same weight among the off-diagonal terms in its calculations. On contrary, $\text{RI}_{\text{NI}}$ is able to balance the error weights on the off-diagonal terms naturally [12]. Therefore, both $\text{RI}_{\text{CBC}}$ and $\text{RI}_{\text{NI}}$ need to be improved in future work.

**VII. Final Remarks**

In a virtual world, plants or trees will be required in evaluations from a quantitative, yet objective, measure. When a virtual tree is constructed, sometimes, a simplified tree is necessary for a real-time or an interactive rendering [20, 30-31]. Previous studies demonstrated that a vegetation rendering with million polygons does require simplified 3D trees for realizing an interactive feature. From viewpoint of a simplified leafy tree if it is far away from the visual point of view, this problem will become inappropriate in this case (zero uncertainty for a single class).

**Remark 11.** When $\text{RI}_{\text{NI}}=0$, one specific case for its corresponding matrix is [12]:

$$h=egin{bmatrix}
0 & h_{0,j} & 0 \\
0 & h_{1,j} & 0 \\
0 & \ldots & 0 \\
0 & h_{j-1,j} & 0 \\
0 & h_{j,j} & 0 \\
0 & h_{j+1,j} & 0 \\
\vdots & \vdots & \vdots \\
0 & h_{L-1,j} & 0 \\
0 & 0 & 0
\end{bmatrix}$$

which means that only one column has non-zero value terms, and all other terms in the matrix are zeros. In this case, one can find that $\text{RI}_{\text{NBC}}>0$.

From the investigations above, we will consider that $\text{RI}_{\text{CBC}}$ is a better measure than $\text{RI}_{\text{NI}}$. However, $\text{RI}_{\text{CBC}}$ also presents some limitations for similarity evaluations. For example, it does not take the error types for mismatching bits into account. $\text{RI}_{\text{CBC}}$ implies the same weight among the off-diagonal terms in its calculations. On contrary, $\text{RI}_{\text{NI}}$ is able to balance the error weights on the off-diagonal terms naturally [12]. Therefore, both $\text{RI}_{\text{CBC}}$ and $\text{RI}_{\text{NI}}$ need to be improved in future work.

**C. Evaluation on a simplified leafy tree**

In apart from modeling evaluations between real-world objects and virtual-world objects, another important perspective of development of an objective measure is from simplification on virtual objects. In the concern of this work, a simplified tree or plant will be required in evaluations from a quantitative, yet objective, measure. When a virtual tree is constructed, sometimes, a simplified tree is necessary for a real-time or an interactive rendering [20, 30-31]. Previous studies demonstrated that a vegetation rendering with million polygons does require simplified 3D trees for realizing an interactive feature. From viewpoint of a simplified leafy tree if it is far away from the visual point of view, this problem will become inappropriate in this case (zero uncertainty for a single class).

**Remark 11.** When $\text{RI}_{\text{NI}}=0$, one specific case for its corresponding matrix is [12]:

$$h=egin{bmatrix}
0 & h_{0,j} & 0 \\
0 & h_{1,j} & 0 \\
0 & \ldots & 0 \\
0 & h_{j-1,j} & 0 \\
0 & h_{j,j} & 0 \\
0 & h_{j+1,j} & 0 \\
\vdots & \vdots & \vdots \\
0 & h_{L-1,j} & 0 \\
0 & 0 & 0
\end{bmatrix}$$

which means that only one column has non-zero value terms, and all other terms in the matrix are zeros. In this case, one can find that $\text{RI}_{\text{NBC}}>0$.

From the investigations above, we will consider that $\text{RI}_{\text{CBC}}$ is a better measure than $\text{RI}_{\text{NI}}$. However, $\text{RI}_{\text{CBC}}$ also presents some limitations for similarity evaluations. For example, it does not take the error types for mismatching bits into account. $\text{RI}_{\text{CBC}}$ implies the same weight among the off-diagonal terms in its calculations. On contrary, $\text{RI}_{\text{NI}}$ is able to balance the error weights on the off-diagonal terms naturally [12]. Therefore, both $\text{RI}_{\text{CBC}}$ and $\text{RI}_{\text{NI}}$ need to be improved in future work.

**VII. Final Remarks**

In a virtual world, plants or trees will be required in evaluations from a quantitative, yet objective, measure. When a virtual tree is constructed, sometimes, a simplified tree is necessary for a real-time or an interactive rendering [20, 30-31]. Previous studies demonstrated that a vegetation rendering with million polygons does require simplified 3D trees for realizing an interactive feature. From viewpoint of

![Fig. 3. Image data for evaluations of a simplified leafy tree:](a) Image of original 3D virtual tree with total 19677 polygons, (b) Image of simplified 3D virtual tree with total 1901 polygons.)
As a preliminary study, this work attempts to establish an objective approach in evaluating synthesized 3D plants/trees from 2D image data. The main contributions of this work are summarized below:

- We proposed strategy for hierarchical evaluations of attributes of objects from image data sets, which will be in compatible with the image-based modeling of 3D plants/trees and simplify the evaluation analysis.
- We defined “Resemblance Index” as evaluation measures using the normalized mutual information (RI) and a coincident-bit-counting criterion (RIc), which present a low computational complexity as O(L^2).
- We investigated the commons and differences between RI and RIC and found out the intrinsic drawbacks of RI as a similarity measure (say, non-monotonicity with respect to the term variables of the joint histogram matrix), which has not been reported in other literature.
- We conducted numerical examples on the geometrical and crown distribution attributes of trunked tree and simplified tree, respectively, which confirmed the proposed approach to be an approximation, yet efficient, assessment for the synthesized accuracy of 3D reconstructed plants/trees.

However, we recognized that the evaluation approach proposed in this work is only effective in the sense of visual appearances between the real objects and virtual objects, rather than in the sense of similarity from the intrinsic features. The similarity study from the intrinsic features, say, on texture of trunks or leaves of a tree, is still an open problem. Important studies are still remained on the intrinsic features, say, on texture of trunks or leaves of a tree, is still an open problem. Important studies are still remained on the following issues in the related subjects:

- To investigate other existing similarity measures in literature and improve the RIs proposed in this work for having desirable properties in evaluations;
- To select proper features in a color space for simple and effective evaluations on other complex attributes of plants/trees from RGB image data sets;
- To develop a feedback approach in modifying the 3D constructed models, or representations, in the “virtual world” based on the 2D image data sets from a “real world”.

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### REFERENCES


