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# New Graph Distance for Deformable 3D Objects Recognition based on Triangle-Stars Decomposition

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## Abstract

We address the problem of comparing deformable 3D objects represented by graphs such as triangular tessellations. We propose a new graph matching technique to measure the distance between these graphs. The proposed approach is based on a new decomposition of triangular tessellations into triangle-stars. The algorithm ensures a minimum number of disjoint triangle-stars, provides improved dissimilarity by covering larger neighbors and allows the creation of descriptors that are invariant or at least oblivious under the most common deformations. The present approach is based on an approximation of the Graph Edit Distance, which is fault-tolerant to noise and distortion, thus making our technique particularly suitable for the comparison of deformable objects. Classification is performed with supervised machine learning techniques. Our approach defines a metric space using graph embedding and graph kernel techniques. It is proved that the proposed distance is a pseudo-metric. Its time complexity is determined and the method is evaluated against benchmark databases. Our experimental results confirm the performances and the accuracy of our system.

*Keywords:* Graph matching, Graph edit distance, Graph decomposition, Graph embedding, Graph metric, Graph classification, Pattern recognition, 3D object recognition, Deformable object recognition, Metric learning

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## 1. Introduction

Comparing 3D objects is one of the most important tasks in 3D object recognition. Objects represented by graphs such as triangular tessellations (Definitions 1, 2), may be compared using graph matching techniques. In a graph, properties are associated with vertices while relationships are represented by edges. Vertices, edges and their attributes are specified according to the underlying application; for instance, vertices may represent points, regions of interest or any other substructure obtained by applying a data reduction process such as segmentation. Edges are associated with vertex connectivity, defining a topological relationship between them, such as proximity, adjacency, etc. Graph matching is the process of finding a correspondence between vertices and edges of two graphs that satisfies a set of constraints, ensuring that substructures in one graph are mapped to similar substructures in the other. Several approaches have been proposed to solve the graph matching problem [1, 2, 3, 4]. Graph edit distance is one of the most celebrated measures for determining such a distance [5, 6, 7, 8]. It is defined as the minimum-cost sequence of edit operations that transforms one graph into another. Tolerance to noise and distortion is one of the advantages of edit distance. Unfortunately, it has a high computational complexity which grows exponentially with the number of vertices [9]. In this paper, we address the problem of comparing deformable 3D objects. The shapes are represented by graphs. We propose a new distance for comparing deformable 3D objects. This distance is based on the decomposition of triangular tessellations into a set of new substructures that we call *triangle-stars*. A triangle-star is a connected component formed by the union of a triangle and the set of its neighboring triangles, depending on the neighborhood order considered. The proposed decomposition offers a parameterizable triangle-stars representation, which is determined by the order assigned to the neighborhood (Definition 7). The resulting number of triangle-stars is much smaller than the number of vertices as well as being smaller than the number of classical stars [10, 11] (Definition 2). As a result, the computational complexity is re-

duced. The proposed dissimilarity measure ensures a better approximation of the Graph Edit Distance. Indeed, considering triangle-stars structures makes it possible to cover a larger neighborhood area and presents a richer local descriptor compared to classical stars [10, 11]. From the proposed distance, it is possible to construct a set of descriptors which are either invariant or at least oblivious under the most common deformations.

A preliminary version of our work appeared in [12]. In the present version, the graph dissimilarity measure and the triangle-stars decomposition method are both improved. Classification is performed using supervised machine learning techniques. Our approach defines a metric space which describes the various objects. Five classifiers were used, namely: the naïve Bayes classifier, the random forest classifier, the gradient boosted trees approach, support vector machine (SVM) and logistic regression. The complexity analysis section has been extended. A new set of experiments has been performed with recent benchmark databases for deformable shape comparison. The remainder of the paper is organized as follows. In Section 2, we briefly review some related works. The proposed decomposition is described in Section 3 while the proposed distance is introduced in Section 4. Time complexity is determined in Section 5. In Section 6, we present and discuss our experimental results while comparing them with some benchmark shape-matching algorithms, for two benchmark databases. Finally, Section 7 concludes the paper.

## 2. Related works

In this section, we briefly review some 3D object recognition methods. We mainly focus on graph-based approaches as they are the most relevant for our technique. For a more exhaustive review, we refer the reader to [13] for 3D object recognition methods and to [9, 14, 15, 16, 17] for pattern recognition and graph matching techniques. Then, we briefly present the algorithms with which our method has been compared.

### 2.1. 3D object recognition related works

60 Three main categories can be distinguished for 3D object comparison techniques [13]: feature-based methods, graph-based methods and others. In the case of feature-based methods, objects are compared using features associated with their geometrical and topological properties. These features may be global, local or spatial maps. In the case of global features and spatial maps, the entire shape is characterized by a unique descriptor while, in the case of local  
65 features, a descriptor is either associated with the vertices, the triangles or any substructure of interest. Various feature-based approaches have been proposed in the literature [18, 19, 20, 21, 22]. Graph-based methods are powerful tools for establishing correspondences between objects and partial shapes as well as  
70 for their invariant description. According to the type of graph considered, several graph-based techniques have been proposed for 3D object comparison [13]. For instance, in some approaches, shapes are reduced to skeletons through a thinning process [23, 24, 25]. The resulting skeletons are compared using graph matching techniques. Other approaches rely on Reeb graphs, which are constructed from mapping functions defined on the shape manifolds [26, 27, 28].  
75 Various segmentation techniques have been proposed in the literature, in which the shapes are segmented into a finite set of components from which a graph is constructed: the segments correspond to the vertices while their topological relationships are represented by the edges. These graphs may be compared  
80 with graph matching techniques [29, 30, 31]. Additional methods have been proposed [13] such as: view-based similarity, volumetric error based similarity, and weighted point set based similarity, among others. In the case of view-based similarity, two 3D objects are considered to be similar if their projections are similar from all possible viewpoints [32, 33, 34]. For volumetric error based  
85 similarity, the distance between two shapes is calculated by estimating the volumetric error between them [35, 36]. On the other hand, in the case of weighted point set based similarity, a distance between two shapes is calculated from a set of descriptors, which consist of weighted 3D points. First, the shapes are decomposed into substructures. Then, each substructure is represented by a

90 weighted point. Finally, the weighted points are matched. The matching process depends on the weight considered. In [37], the weight represents the volume of the component, in [38], a measure for curvature is used as a weight, while in [39], the authors consider a hierarchy of weighted point sets, representing spherical object approximations.

## 95 2.2. *Benchmark for shape-matching algorithms*

The proposed approach has been compared to various benchmark algorithms associated with SHREC competitions. These algorithms correspond to the two benchmark databases used for their evaluations, namely the TOSCA database [40, 41] and the SHREC11 watertight database [42]. Consequently, our method 100 has been compared with the following algorithms: **CAM** [43]: An approach in which surfaces are represented by 3D curves extracted around feature points. **GeodesicD2**: A global description which consists of distribution of the geodesic distances associated with a given 3D shape. This approach is an extension of Euclidean D2 [44]. **DSR** [45]: The Hybrid Feature Vector is a combination 105 of two view-based descriptors: a depth buffer for the silhouette and a radialized extent function descriptor. **RSH** [46]: The Ray-based approach with Spherical Harmonic Representation is a method which aligns the models into a canonical position, determines the maximal extents and applies a spherical harmonic decomposition. **TD** [47]: The Temperature Distribution descriptor is 110 a shape descriptor based on the heat kernel. The L2 norm is used to evaluate the distance between the descriptors. **Shape-DNA** [48]: The Shape-DNA is a numerical fingerprint obtained by evaluating the eigenvalues of the Laplace-Beltrami operator associated with the manifold. The matching between two objects is obtained by comparing their respective eigenvalues. **SRCP-TD** [49]: 115 The SRCP-TD is a method based on a sparse representation of a scale-invariant heat kernel. The authors use Laplace-Beltrami eigenfunctions to detect critical points on the manifold. The descriptor is constructed from the heat kernel values at these points. A sparse representation is employed to reduce the dimensionality of the descriptor.

### 120 **3. Algorithm description: new decomposition into triangle-stars**

In this section, we propose a new decomposition of triangular tessellations into connected components that we call *triangle-stars*. This decomposition aims to reduce the number of components while covering larger neighborhoods. The extent of the neighborhood associated with a triangle-star is determined by its order  $N_k$ . From this representation, it is possible to define a description  
125 which is invariant or at least oblivious under the most common deformations. Prior to decomposition, a strict total order on the triangles must be established. This order aims to reduce the number of triangle-stars that is generated while guaranteeing the uniqueness of the decomposition.

#### 130 **3.1. Triangle-star**

We propose to decompose graphs such as triangular tessellations into a set of connected components that we call triangle-stars (*TS*). Triangle-stars are defined from the following set of definitions:

**Definition 1 (Graph).** A graph  $G$  is a set of vertices connected by a set of  
135 edges. Formally, a graph  $G$  is a four tuple  $G = (V, E, \alpha, \beta)$ , where:  $V$  and  $E \subseteq V \times V$  are the vertices and edges.  $\alpha : V \rightarrow L_V$  and  $\beta : E \rightarrow L_E$  are labeling functions associated with the vertices and edges, respectively [50].

**Definition 2 (Star).** A classical star  $S$  is a labeled, single-level, tree formed by a root vertex  $r$ , the set of leaves or mono-degree vertices  $L$  and the set of  
140 edges  $E$  connecting the root vertex with any vertex belonging to  $L$ . Figure 1 shows all the classical stars that may be constructed from a given graph  $G$  [10, 11].

**Definition 3 (Triangular tessellations).** A triangular tessellation  $G_{tr}$  is a graph defined by a set of vertices, edges and triangles. Formally,  $G_{tr}$  is a  
145 graph defined by a six tuple  $G_{tr} = (V, E, T, \alpha, \beta, \theta)$ , where:  $V$ ,  $E$  and  $T$  are the vertices, edges and triangles, respectively.  $\alpha : V \rightarrow L_V$ ,  $\beta : E \rightarrow L_E$  and  $\theta : T \rightarrow L_T$  are their corresponding labeling functions.

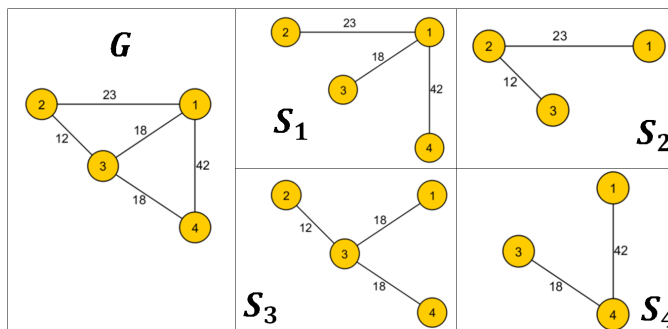


Figure 1: Classical stars associated with a graph.

**Definition 4 (neighborhood of a triangle).** Two triangles are neighbors if they share at least one common vertex. Let  $t_1$  and  $t_2$  be two triangles and  $V(t_1)$  and  $V(t_2)$  their respective vertices. Then,  $t_1$  and  $t_2$  are *neighbors* 150  $\Leftrightarrow \|V(t_1) \cap V(t_2)\| > 0$ . In other words, the neighborhood ( $N$ ) of a triangle  $t$  consists of all the triangles sharing at least one common vertex with  $t$ .

**Definition 5 ( $N_k$ -neighborhood of a triangle).** Two triangles  $t_0$  and  $t_k$  are  $N_k$ -neighbors if between  $t_0$  and  $t_k$  there is a chain of at most  $(k - 1)$  distinct 155 triangles, which are pairwise consecutive neighbors. Formally,  $t_0$  and  $t_k$  are  $N_k$ -neighbors  $\Leftrightarrow \exists t_{i=1\dots k-1}$  where :  $\forall i \in 1\dots(k - 1)$ ,  $t_i$  and  $t_{i+1}$  are neighbors. In the case of  $k = 1$ , the  $N_k$ -neighborhood is reduced to a simple neighborhood (Definition 4).

**Definition 6 (triangle-star).** A triangle-star  $ts$  is a labeled subgraph, defined 160 by a triangle and the set formed by its neighbors. Formally, a triangle-star  $ts$  is a three tuple  $ts = (t_r, T', \theta)$ , where:  $t_r$  is the root triangle,  $T'$  is the set of adjacent triangles and  $\theta : T \rightarrow L_T$  is the triangle labeling function, while  $L_T$  is a set of labels.

**Definition 7 ( $N_k$ -triangle-star).** A  $N_k$ -triangle-star  $N_k$ - $ts$  is a triangle-star 165 defined by a triangle and the set of its  $N_k$ -neighbors. In the case of  $k = 1$ , the  $N_k$ -triangle-star is a simple triangle-star (Definition 6). See, for instance, the following example.



**Example 1.** Consider a graph-tessellation  $G_{tr}$  containing 17 triangles  $t_0 \dots t_{16}$ . Table 1 shows the graph-tessellation  $G_{tr}$  and the corresponding  $N_k$ -triangle-stars associated with the triangle  $t_0$  according to the order  $N_{k=0 \dots 2}$  of the corresponding neighborhood. In the case  $N_{k=0}$ , the graph-tessellation is decomposed into 17 triangle-stars. Each triangle-star consists of a single triangle which means that no neighborhood is considered. Therefore, the triangle-star  $N_0$ - $TS$  associated with the triangle  $t_0$  is the very same triangle  $t_0$ . When  $N_{k=1}$ , only the closest neighborhood is employed for the construction of the triangle-stars (See Definition 4). Thus, the triangle-star  $N_1$ - $TS$  associated with the triangle  $t_0$  is formed by the triangle  $t_0$  and its  $N_1$ -neighbors (direct neighbors), *i.e.*,  $T(N_1-TS) = \{t_0 \dots t_7\}$ . In the case  $N_{k=2}$ , the  $N_2$ -neighborhoods are considered, which means that the graph-tessellation is decomposed into a set of triangle-stars formed by the root triangle and its  $N_2$ -neighbors (See Definition 5). As a result, the triangle-star  $N_2$ - $TS$  associated with the triangle  $t_0$ , is formed by the triangle  $t_0$  and its  $N_2$ -neighbors (second order neighborhood).  $T(N_2-TS) = \{t_0 \dots t_{16}\}$ .

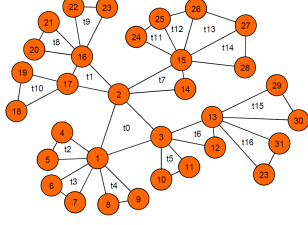
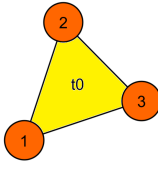
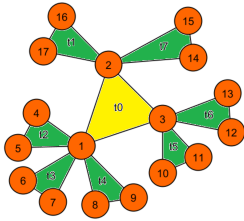
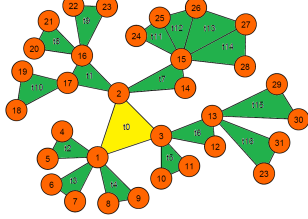
Graph $G_{tr}$	$N_0$ - $TS$ of triangle $t_0$
	
$N_1$ - $TS$ of triangle $t_0$	$N_2$ - $TS$ of triangle $t_0$
	

Table 1: Example of  $N_k$ -triangle-stars.

**Triangle-star features.** A six-tuple  $t_j = (v_1, v_2, v_3, e_1, e_2, e_3)$  is associated with each triangle  $t_j$ . The vertices  $v_i$  are labeled by their respective Cartesian  
185 coordinates  $v_i = (x, y, z)$ , while the edges  $e_k = (v_p, v_w)$  are labeled (weighted) with the Euclidean in distance between their respective vertices  $(v_p, v_w)$ . The triangles are labeled with a three-tuple  $t_j = (id, Area, Perimeter)$ , where  $id$  is a number. Each triangle-star is characterized by a set of descriptors, allowing for evaluation of the dissimilarity between triangle-stars. We consider the fol-  
190 lowing descriptors: Area of triangle-star, Perimeter of triangle-star, Area of the triangles forming the triangle-stars, their Perimeters, the Weights associated with their edges, and the Degrees of their vertices. Our choice of descriptors is justified by the fact that these quantities are oblivious under the most common deformations.

**Triangle-star vector representation.** A vector is associated with each triangle-  
195 star. This vector consists of the global area  $AG$  and the global perimeter  $PG$  of the triangle-star, the area  $A$  and the perimeter  $P$  of each triangle belonging to the triangle-star, the weights associated with their edges  $W$ , as well as the degrees  $Deg$  associated with their vertices. This vector is given by:

$$200 \quad \{AG(ts), PG(ts), \{A(t_i), P(t_i), W(t_i, j=1\dots 3), Deg(t_i, j=1\dots 3)\}_{i=1}^{i=\|T(ts)\|}\}$$

The various variables are described in Table 2. The triangles belonging to the triangle-star  $ts$  are ranked according to their areas in descending order. The weights and the degrees are ranked in descending order as well. All triangle-stars  $TS$  vectors have the same size:  $size = 2 + (8 \Gamma)$ , where  $\Gamma$  is the maximum  
205 number of triangles in the triangle-stars. If a triangle-star  $ts$  has a number of triangles less than  $\Gamma$ , the unassigned entries are completed with *zeros*.

**Definition 8 (Disjoint triangle-stars).** Two triangle-stars  $ts_i$  and  $ts_j$  are *disjoints* if they do not share, at least, a common triangle. Let  $i \neq j$ , if  $ts_i$  and  $ts_j$  are *disjoints*  $\Rightarrow T(ts_i) \cap T(ts_j) = \emptyset$ .

Symbol	Description
$t_{i,t}$	Triangle $t_l$ belonging to the triangle-star $ts_i$ : $t_l \in ts_i$
$W_{i,t,k}$	Weight (Euclidean distance) of edge $e_k$ belonging to triangle $t_l \in ts_i$
$Deg_{i,t,k}$	Degree of vertex $v_k$ belonging to triangle $t_l \in ts_i$
$\Gamma$	Max number of triangles in the triangle-stars
$\alpha \in \mathbb{R}_+^6$	Parameters associated with the descriptors where $ \alpha _1 = 1$
$A(t_i)$	Area of triangle $i$ .
$P(t_i)$	Perimeter of triangle $i$ .
$AG(ts_i)$	Area of triangle-star $i$ . $AG(ts_i) = \sum_{j=1}^{j=\ T(ts_i)\ } A(t_j)$
$PG(ts_i)$	Perimeter of triangle-star $i$ . $DG(ts_i) = \sum_{j=1}^{j=\ T(ts_i)\ } D(t_j)$

Table 2: Quantities associated with the dissimilarity measure and their description.

### 210 3.2. Triangle ordering

The proposed decomposition generates disjoint triangle-stars (Definition 8), which significantly reduces the number of components ( $\|TS\| \ll \|V\| < \|T\|$ ) as well as the number of comparisons involved when matching two graphs. However, depending on the ordering considered, the triangle-stars obtained may differ (see Example 2). Indeed, the same triangular tessellation may generate  
215 different sets of triangle-stars if the ordering of the triangles is not identical.

In order to ensure the **uniqueness** of the decomposition and to further reduce the number of triangle-stars, a strict descending total order must be established on the set of triangles prior to their decomposition into triangle-stars.  
220 Considering a  $\|Neighbors(Triangles)\|$  with *descending order* results in the smallest number of triangle-stars  $TS$  (as demonstrated in the experimentations), thus further contributing to the reduction of computational complexity.

In order to establish a strict descending total order on the set of triangles, each triangle  $t_i$  is represented by a vector  $\{\|N(t_i)\|, \{x_{i,j}, y_{i,j}, z_{i,j}\}_{j=1}^{j=3}\} \in \mathbb{R}^{10}$   
225 which corresponds to the number of neighbors  $\|N(t_i)\|$  and to the Euclidean coordinates  $x, y, z$  associated with the vertices forming the triangle  $t_i$ . Naturally, the coordinates and consequently the ordering may be affected by a rotation of the object. In order to eliminate this problem, the coordinates are expressed in the reference frame defined by the Eigen vectors of the tensor of inertia associated with the vertices. The number of neighbors  $\|N(t_i)\|$  is used to further  
230

reduce the number of triangle-stars. If two triangles have the same number of neighbors, the vertex coordinates are used to ensure the uniqueness of the decomposition. The vertices in the vector (10-tuple) are lexicographically ordered according to their coordinates.

**Example 2.** Let us consider a triangle  $t_0$  with  $n$  neighbors  $t_1 \dots t_n$  (Figure 2).

If we consider a triangle order based on the number of neighbors with descending order, we obtain only one triangle-star, else three triangle-stars are obtained.

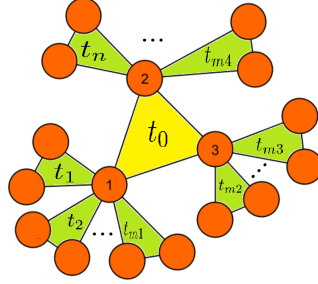


Figure 2: A triangle  $t_0$  with  $n$  triangular neighbors.

235 **3.3. Triangle-stars decomposition**

Once the strict total order of the triangles has been established, the decomposition of the graph into triangle-stars may be performed. This process is described in Algorithm 1. According to the order established for the triangles (strict descending order), the first  $N_k$ -triangle-star is constructed from the first  
 240 triangle and its corresponding  $N_k$ -neighbors (Definition 7); that is, the triangles not belonging to any other  $N_k$ -triangle-stars. Then, the set of triangles and the set of the resulting  $N_k$ -triangle-stars are updated. The process is repeated until a  $N_k$ -triangle-star is associated with each triangle.

The proposed decomposition generates a reduced number of triangle-stars  
 245  $ts$  as opposed to the number of vertices  $\|TS\| \ll \|V\|$ . The resulting triangle-stars are disjoint (Definition 8) and cover a larger local area than the classical stars (Definition 2). This decomposition is also parameterizable through the neighborhood order. Indeed, the higher the neighborhood order, the smaller the number of triangle-stars ( $\|N_{k+1}-TS\| \leq \|N_k-TS\|$ ) which, in turn, cover  
 250 a larger neighborhood ( $\|T(N_{k+1}-TS)\| \geq \|T(N_k-TS)\|$ ). In addition, the proposed decomposition is unique.

---

**Algorithm 1** Graph decomposition into  $N_k$ -triangle-stars.

---

1: **Inputs:** A graph  $G_{tr}$  and the neighborhood order  $N_k$ .  
2: **Outputs:** A set of  $N_k$ -triangle-stars ( $N_k$ - $TS$ ).  
3: **Begin**  
4:     Apply a **descending** strict total order on the set of triangles of  $G_{tr}$ ;  
5:      $N_k$ - $TS = \emptyset$  ;  
6:     **while** ( $T(G_{tr}) \neq \emptyset$ ) **do**  
7:          $t_i = T(G_{tr})[0]$   
8:          $T(N_k$ - $ts_i) = t_i \cup N_k$ -**neighbors**( $t_i$ ) ;  
9:          $N_k$ - $TS = N_k$ - $TS \cup N_k$ - $ts_i$  ;  
10:         $T(G_{tr}) = T(G_{tr}) - T(N_k$ - $ts_i)$  ;  
11:     **end while**  
12:     return  $N_k$ - $TS$  ;  
13: **End**

---

**Example 3.** We consider a triangular tessellation defined as follows:

$G_{tr} = \{16 \text{ vertices, } 20 \text{ triangles } t_{1..20}\}$  as shown in Table 3. The decomposition into triangle-stars ( $N_1$ - $TS$ ) begins with the construction of the first  
255 triangle-star  $TS_1$  using the triangle  $t_{13}$  as the root triangle and its corresponding  $N_1$ -neighborhood. The triangle  $t_{13}$  is selected as the root triangle since it has the maximum number of neighbors, which is 12 in this particular case. The next triangle with the maximum number of neighbors (seven) is  $t_1$ ; this triangle is employed for the construction of the second triangle-star  $TS_2$ .  $TS_2$  is constructed using  $t_1$  and its 3 neighbors. The third triangle-star  $TS_3$  is formed by  
260  $t_{11}$  and its neighbors:  $t_{11}$  had 5 neighbors which is the maximum number of neighbors in the remaining set of triangles.  $TS_3$  is constructed using  $t_{11}$  and its 2 remaining neighbors. In the case of the  $N_2$ -neighborhood, we obtain one triangle-star  $N_2$ - $TS_1$  formed by the triangle  $t_{13}$  and its  $N_2$ -neighborhood which  
265 consists of all the triangles belonging to  $G_{tr}$ . Therefore,  $N_2$ - $TS_1$  is equivalent to the triangular tessellation  $G_{tr}$  in this particular case.

**Example 4.** Table 4 shows the correspondence in between  $N_2$ -triangle-stars of two poses centaur0 and centaur3 of the same object centaur belonging to the TOSCA Database.

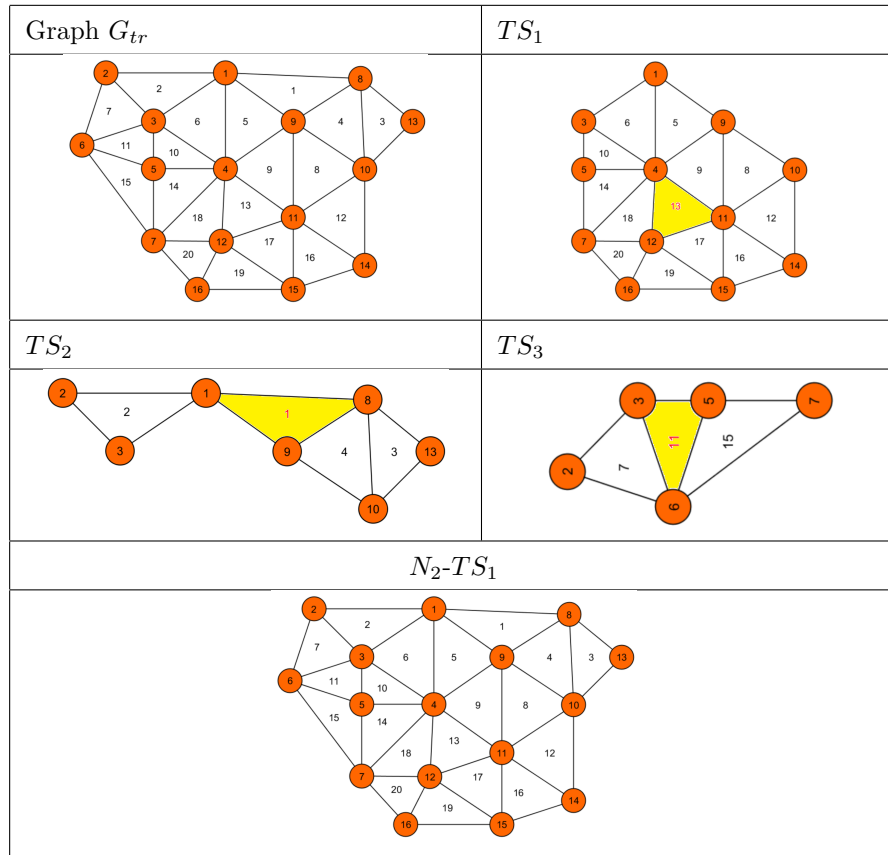


Table 3: Decomposition of a graph into a set of  $N_1$  and  $N_2$ -triangle-stars.

270 **4. Algorithm description: new distance for triangular tessellations**

In this section we propose a novel distance between the triangle-stars of two triangular tessellations to address their matching. We prove that the proposed distance ( $TSM$  for *Triangle-Star Measure*) is a pseudo-metric.

**4.1. Edit distance between triangle-stars**

We first introduce the graph edit distance between triangle-stars. The proposed dissimilarity measure is defined to be applicable to deformable objects. As a result, the set of descriptors must be invariant or at least oblivious under the most common deformations. The dissimilarity measure is based on the fol-

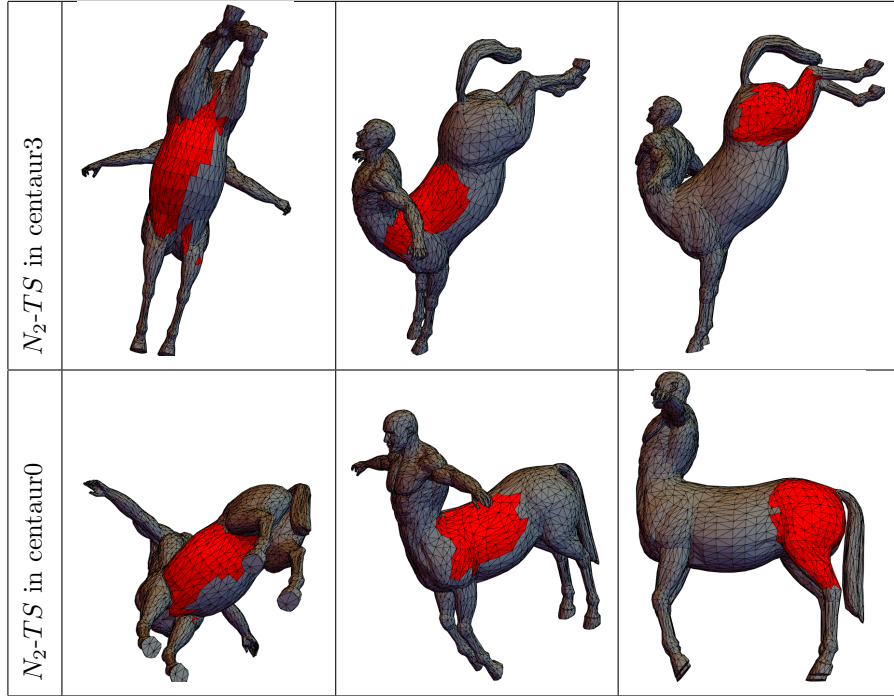


Table 4: The correspondence between  $N_2$ -triangle-stars (colored in red) of two poses centaur0 and centaur3 of the same object centaur belonging to the TOSCA Database.

lowing parameters: *Area* and *Perimeter* of triangle-star, *Area* and *Perimeter* of triangles, *Weights* of edges and *Degrees* of vertices. Formally a triangle-star is represented as follows:  $\{AG(ts), PG(ts), \{A(t_i), P(t_i), W(t_i, j=1..3), Deg(t_i, j=1..3)\}_{i=1}^{\|T(ts)\|}\}$ . The dissimilarity measure  $d$  between two triangle-stars  $ts_i$  and  $ts_j$  is defined as:

$$d(ts_i, ts_j) = \sum_{k=1}^{k=6} dsim_k (ts_i, ts_j) \quad (1)$$

275

The dissimilarity measure  $d$  is normalized ( $0 \leq d \leq 1$ ) and requires the def-

inition of six auxiliary functions  $dsim_k$ . These functions are defined as follows:

$$dsim_k(ts_i, ts_j) = \begin{cases} \alpha_1 \frac{|AG(ts_i) - AG(ts_j)|}{AG_{MAX}} & \text{if } k = 1 \\ \alpha_2 \frac{|PG(ts_i) - PG(ts_j)|}{PG_{MAX}} & \text{if } k = 2 \\ \alpha_3 \frac{\sum_{l=1}^{\Gamma} |A(T(ts_i)_l) - A(T(ts_j)_l)|}{A_{MAX} \Gamma} & \text{if } k = 3 \\ \alpha_4 \frac{\sum_{l=1}^{\Gamma} |P(t_{i,l}) - P(t_{j,l})|}{P_{MAX} \Gamma} & \text{if } k = 4 \\ \alpha_5 \frac{\sum_{l=1}^{\Gamma} \sum_{k=1}^{k=3} |W_{i,l,k} - W_{j,l,k}|}{3 W_{MAX} \Gamma} & \text{if } k = 5 \\ \alpha_6 \frac{\sum_{l=1}^{\Gamma} \sum_{k=1}^{k=3} |Deg_{i,l,k} - Deg_{j,l,k}|}{3 Deg_{MAX} \Gamma} & \text{if } k = 6 \end{cases} \quad (2)$$

$dsim_1(ts_i, ts_j)$  and  $dsim_2(ts_i, ts_j)$  compare respectively the Area  $AG$  and the Perimeter  $PG$  of two triangle-stars  $ts_i$  and  $ts_j$ .  $dsim_3(ts_i, ts_j)$  and  $dsim_4(ts_i, ts_j)$  compare respectively the Area  $A$  and the Perimeter  $P$  of their respective triangles. While  $dsim_5(ts_i, ts_j)$  and  $dsim_6(ts_i, ts_j)$  compare respectively the Weights  $W$  associated with their respective edges and the Degree  $Deg$  of the corresponding vertices. The symbols associated with the dissimilarity measure are defined in Table 2.

Graph Edit Distance (GED) is based on a set of classical edit operations namely: insertion, deletion and substitution of vertices and/or edges. The proposed dissimilarity measure  $d(ts_i, ts_j)$  (Eq. 1) is equivalent to a substitution edit operation of two triangle-stars  $ts_i$  and  $ts_j$ . However, the insertion edit operation of a triangle-star  $ts_i$  is equivalent to replacing an empty triangle-star  $\varepsilon$  by  $ts_i$  which, in turn, is equivalent to the dissimilarity measure  $d(\varepsilon, ts_i)$ . Analogously, the deletion edit operation of a triangle-star  $ts_i$  is equivalent to replacing  $ts_i$  by an empty triangle-star  $\varepsilon$ , which is equivalent to the dissimilarity measure  $d(ts_i, \varepsilon)$ . The six auxiliary functions  $dsim_k$  (Eq. 2) are equivalent to a substitution of two triangle-stars  $ts_i$  and  $ts_j$   $dsim_k(ts_i, ts_j)$ , a deletion or an insertion of a triangle-star  $ts_i$   $dsim_k(ts_i, \varepsilon)$  by considering, separately, one of the six parameters ( $AG$ ,  $PG$ ,  $A$ ,  $P$ ,  $W$  and  $Deg$ ). Consequently, the dimensions of the cost matrix  $D$  are reduced and we obtain a better time complexity, see Section 5.

**Scale invariance.** The dissimilarity measure  $d$  (Eq. 1) is sensitive to scale, which means that if two triangle-stars  $ts_i$  and  $ts_j$  have the same structure



but a different scale, they are not considered to be similar. In order to obtain  
 300 scale invariance, the weights  $W$  must be normalized, which means formally that  
 $\forall i, W_i = \frac{W_i}{W_{MAX}}$ . Consequently, by normalizing weights  $W$ , the parameters  $AG$ ,  
 $PG$ ,  $A$  and  $P$  are also normalized.

#### 4.2. Edit distance between two triangular tessellations

The calculation of the distance between two triangular tessellations repre-  
 305 sented by triangle-stars constitutes the last step of our algorithm. We call this  
 dissimilarity measure *Triangle-Star Measure TSM*. This measure determines  
 the best possible matching between two sets of triangle-stars. The dissimilarity  
 between two sets of triangle-stars is defined as follows:

**Definition 9 (TSM).** Let  $g_{T_1}$  and  $g_{T_2}$  be two triangular tessellations,  $TS_1$   
 and  $TS_2$  their corresponding sets of triangle-stars,  $M$  the set of all possible  
 matchings between  $TS_1$  and  $TS_2$ , and  $m \in M$  the mapping function. The  
 dissimilarity measure  $TSM(TS_1, TS_2)$  (normalized dissimilarity) is defined as:

$$TSM(TS_1, TS_2) = \frac{\min_{m \in M} \sum_{ts_i \in TS_1, m(ts_i) \in TS_2} d(ts_i, m(ts_i))}{\max(\|TS_1\|, \|TS_2\|)} \quad (3)$$

The computation of  $TSM(TS_1, TS_2)$  is equivalent to solving the assign-  
 310 ment problem, which is one of the fundamental combinatorial optimization prob-  
 lems that aim to find the minimum/maximum weight matching in a weighted  
 bipartite graph. To solve this assignment problem, we define a  $n \times n$  ma-  
 trix  $D$ , where  $n$  is given by  $n = \max(\|TS_1\|, \|TS_2\|)$ . Each element  $D_{i,j}$  of  
 the matrix represents the dissimilarity measure  $d(ts_i, ts_j)$  (Eq. 1) between a  
 315 triangle-star  $ts_i$  in  $TS_1$  and a corresponding triangle-star  $ts_j$  in  $TS_2$ . In the  
 case of  $\|TS_1\| \neq \|TS_2\|$ , the smallest set of triangle-stars is completed by  
 $(\max(\|TS_1\|, \|TS_2\|) - \min(\|TS_1\|, \|TS_2\|))$  empty triangle-stars  $\varepsilon$ . The dis-  
 tance between an empty triangle-star  $\varepsilon$  and a triangle-star  $ts$  is computed by  
 Eq. 1 and corresponds to the cost of adding  $ts$  to the small set of triangle-stars  
 320 (or deleting  $ts$  from the large set of triangle-stars).

We apply the Hungarian algorithm [51] to the matrix  $D$  to find the best assignment in  $\mathcal{O}(n^3)$  time. The evaluation of the distance between two graphs (triangle tessellations), is summarized in Algorithm 2.

The classification is then performed using supervised machine learning techniques. Our approach defines a metric space which describes the various objects, using graph embedding and graph kernel techniques: Each object (the set of its triangle-stars)  $TS_i$  is mapped onto a vector space, where it is represented by a vector of distances  $TSM(TS_i, TS_{j=1\dots n})$ , between  $TS_i$  and the set of other objects  $TS_{j=1\dots n}$ .

---

**Algorithm 2** The distance between two graphs using TSM.

---

```

1: Inputs: Two graphs  $g_1$  and  $g_2$ .
2: Outputs: The distance between  $g_1$  and  $g_2$ .
3: Begin
4:   Decomposition of  $g_1$  and  $g_2$  into sets of triangle-stars  $TS_1$  and  $TS_2$ , (Algo. 1).
5:   Construct a matrix of distance  $D$ .
6:   For each  $ts_i \in TS_1$  and  $ts_j \in TS_2$  do
7:      $D_{i,j} = d(ts_i, ts_j)$  (Eq. 1);
8:   end For each
9:   Solving (Eq. 3), by applying the Hungarian algorithm [51] on the matrix  $D$ .
10:  return the distance  $TSM(TS_1, TS_2)$  ;
11: End

```

---

### 330 4.3. The Pseudo-metric

In this section we prove that the proposed distance is a **pseudo-metric**.

**Definition 10 (Pseudo-metric)** Let  $X$  be a set of objects and  $x, y, z \in X$ . Let  $f$  be a function defined as follows  $f : X \times X \rightarrow \mathbb{R}$ . Let the following set of properties: (1) **non-negativity:**  $f(x, y) \geq 0$ , (2) **symmetry:**  $f(x, y) = f(y, x)$ , (3) **triangle inequality:**  $f(x, y) \leq f(x, z) + f(z, y)$  and (4) **uniqueness:**  $f(x, y) = 0 \Rightarrow x = y$ . The function  $f$  is a metric if  $f$  satisfies these four properties, while  $f$  is a pseudo-metric if  $f$  satisfies only the first three properties (1, 2 and 3).

340 Since  $f$  is a pseudo metric, a distance function may be defined between each pair of graphs. As a result, the dissimilarity between graphs may be efficiently determined. [52, 53].

**Lemma:** The proposed similarity measure  $TSM$  (Eq. 3) between two sets of triangle-stars  $TS_1$  and  $TS_2$  is a **pseudo-metric**.

345 **Proof:** From (Eq. 3) it may be concluded that if  $TSM$  is a pseudo-metric then  $d$  (Eq. 1) is a pseudo-metric, which implies that  $dsim_k$  (Eq. 2) are pseudo-metrics. Consequently, we shall prove that  $dsim_k$  (Eq. 2) are pseudo-metrics. Proving that  $dsim_k$  (Eq. 2) are pseudo-metrics is equivalent to ensuring that the first three properties are satisfied. The functions  $dsim_k$  are defined as follows:

350  $dsim_k = \alpha_k * \frac{|x_1 - x_2|}{\beta}$  with  $x_1, x_2, \in \mathbb{R}_+$ ,  $\alpha_k, \beta \in \mathbb{R}_+^*$ .

1) **non-negativity:**  $TSM(TS_1, TS_2) \geq 0$ . We have  $dsim_k \geq 0 \Rightarrow TSM \geq 0$ . Thus  $TSM$  is non-negative. 2) **symmetry:**  $TSM(TS_1, TS_2) = TSM(TS_2, TS_1)$ .

The proposed decomposition is unique and the  $TSM$  is only based on symmetrical operations (addition and subtraction in absolute value). Consequently,  $TSM$  is symmetrical. 3) **triangle inequality:**  $TSM(TS_1, TS_2) \leq TSM(TS_1, TS_3) + TSM(TS_3, TS_2)$ . We have the triangle inequality verified in:  $|x_1 - x_2| \leq |x_1 - x_3| + |x_3 - x_2|$ . Thus, the triangle inequality is verified in  $dsim_k$  and we have:  $TSM(TS_1, TS_2) \leq TSM(TS_1, TS_3) + TSM(TS_3, TS_2)$ . Consequently, the triangle inequality is verified in  $TSM$ .

## 360 5. Computational complexity

The most demanding part of the algorithm, in terms of time complexity, is the one solving the assignment problem. As mentioned earlier, the Hungarian algorithm [51] is employed to find the best assignment in  $\mathcal{O}(n^3)$  time, where  $n$  is the *maximum* number of components in the two graphs. Let 365  $n = \max(\|V_1\|, \|V_2\|)$  and  $n' = \max(\|TS_1\|, \|TS_2\|)$ , where  $V_i$  is the set of vertices and  $TS_i$  is the set of triangle-stars in  $g_{tr\ i}$ . In the proposed decomposition, any triangle-star has at least one triangle. Consequently, in the

worst case, we have  $n' = \frac{n}{3}$ , which means that complexity is of the order of  $\mathcal{O}(0.037 n^3)$ . However, the number of triangle-stars depends on the structure of the underlying graph as well as on the neighborhood order  $N_k$ . Indeed, the number of triangle-stars decreases when the neighborhood order  $N_k$  increases. The computational complexity, for the TOSCA database [40, 41], is of the order of  $\mathcal{O}(\alpha \lfloor \frac{n}{\log(n)} \rfloor^3)$ , where  $\alpha \in [1.80 * 10^{-7}, 0.74]$  for  $N_{k=1\dots 6}$ :  $\mathcal{O}(0.74 \lfloor \frac{n}{\log(n)} \rfloor^3)$  for  $N_1$ ,  $\mathcal{O}(0.0001 \lfloor \frac{n}{\log(n)} \rfloor^3)$  for  $N_2$ ,  $\mathcal{O}(5.6115 * 10^{-6} \lfloor \frac{n}{\log(n)} \rfloor^3)$  for  $N_3$ ,  $\mathcal{O}(9.84 * 10^{-7} \lfloor \frac{n}{\log(n)} \rfloor^3)$  for  $N_4$ ,  $\mathcal{O}(3.59 * 10^{-7} \lfloor \frac{n}{\log(n)} \rfloor^3)$  for  $N_5$  and  $\mathcal{O}(1.80 * 10^{-7} \lfloor \frac{n}{\log(n)} \rfloor^3)$  for  $N_6$ . As shown above, the complexity decreases when the neighborhood order  $N_k$  increases: the neighborhood order  $N_{k=1}$  has the highest complexity while the neighborhood order  $N_{k=6}$  has the lowest.

Computing the exact value of the graph edit distance GED is NP-Hard for general graphs which implies an exponential computational complexity [11]. As a result, several algorithms approximating GED in polynomial time have been suggested. We propose a new graph distance, which is an approximation of GED (bipartite graph matching) based on triangle-star (TS) decomposition. The proposed dissimilarity measure  $d(ts_i, ts_j)$  (Eq. 1) is equivalent to a substitution edit operation of two triangle-stars  $ts_i$  and  $ts_j$ . The insertion and deletion edit operation is equivalent to replace an empty triangle-star  $\varepsilon$  by  $ts_i$   $d(\varepsilon, ts_i)$  (for insertion) and replacing  $ts_i$  by an empty triangle-star  $\varepsilon$   $d(ts_i, \varepsilon)$  (for deletion), respectively. Consequently, the dimensions of the cost matrix  $D$  are reduced to  $n \times n$ , where  $n$  is given by  $n = \max(\|TS_1\|, \|TS_2\|)$  ( $\|TS\| \ll \|V\|$ ). Therefore, we obtain a better time complexity than the state of the art. Indeed, in [10] and [11], the complexity achieved is  $\mathcal{O}((n + m)^3)$ , where  $n$  and  $m$  are the number of nodes in the two graphs. In [54] and [55], the obtained complexity is  $\mathcal{O}((\max(n, m))^3)$ . However, the Jonker-Volgenant linear solver [56] has some convergence problems for some specific cost matrices. In [57], the proposed algorithm has a quadratic computational cost  $\mathcal{O}(n * m)$ . However, it does not generate a bijective correspondence between the nodes of the two graphs. In [58], the complexity achieved is:  $\mathcal{O}((\min(n, m))^2 \max(n, m))$ . Our approach obtains a better time complexity than [58], except from when

$\|n - m\| \in ]1600, 4000[$ , for which the complexity is  $\mathcal{O}(0.037 n^3)$ ) and, when  
 400  $\|n - m\| \in ]1700, 3900[$  and  $N_{k=1}$ , for which the complexity is  $\mathcal{O}(0.74 \lfloor \frac{n}{\log(n)} \rfloor^3)$ .  
 However, these intervals are not present in our experimentations (TOSCA and  
 SHREC databases).

## 6. Experimental results

To evaluate the proposed approach, we undertook a set of experimentations  
 405 in which we compared our approach with some benchmark algorithms for shape-  
 matching, under different evaluation criteria, for two benchmark databases,  
 namely the TOSCA database [40, 41] and the SHREC11 watertight database  
 [42].

### 6.1. Database description

410 In this section, we describe the two benchmark databases utilized in our  
 evaluation: TOSCA and SHREC11 watertight databases.

The TOSCA database [40, 41] consists of 148 three-dimensional objects.  
 Each object is represented by a triangular tessellation. The database consists of  
 12 classes. Each class is composed of the same object submitted to isometric or  
 415 quasi-isometric deformations. The database is unbalanced (from 3 to 24 objects  
 per class). On average, the number of vertices is 3154 while the number of  
 triangles is 6220.

The SHREC11 watertight database [42] consists of a relatively large collec-  
 tion of non-rigid 3D shapes. This database was created from several publicly  
 420 available databases such as the McGill database [59], the TOSCA database  
 [40, 41] and the Princeton Shape Benchmark [60]. The SHREC11 watertight  
 database [42] consists of 600 non-rigid objects represented by triangular tessel-  
 lations. The database is balanced: it is formed by 30 classes, each consisting of  
 20 poses of the same object.

425 **6.2. Experimental results**

In this section, we compare and discuss our results with those obtained with the following benchmark databases: TOSCA [40, 41] and SHREC11 watertight [42]. The proposed distance  $TSM$  is parameterized through the parameters  $\alpha_k$ , which determine the weights assigned to the various similarity measures. The default value for these parameters is:  $\alpha_k = 1/6, \forall k$ . As proved earlier, the  $TSM$  distance is a pseudo-metric. In order to classify the various objects belonging to the benchmark databases, the metric is learned with machine learning techniques. This is in contrast with the standard approach in which an invariant descriptor is associated with each object and classification is performed with machine learning techniques through supervised learning. In our approach, the  $TSM$  distance defines a metric space which describes the various objects. Therefore, in order to perform classification, the metric must be learned using a supervised learning process. Five classifiers were evaluated in order to determine their suitability for metric learning, namely: the naïve Bayes classifier, the random forest classifier, the gradient boosted trees approach, support vector machine (SVM) and logistic regression. These classifiers have been extensively described in the literature [61, 62]. Therefore, we shall limit ourselves to a high level description. In what follows, the features refer to the metric. The naïve Bayes (NB) classifier [61, 62] is a probabilistic classifier based on the Bayes' theorem. It assumes that the features are generated independently given the class and uses the Bayes theorem to predict the class. The random forest (RF) classifier [61, 62] uses a set of decision trees to predict the class. Each decision tree has been trained on a random subset of the training set, and only uses a random subset of the features. The gradient boosted tree (GBT) classifier [61, 62] predicts labels by iteratively training a sequence of decision trees on training data and combining them. The support vector machine (SVM) classifier [61, 62] separates the training set into two classes using a maximum-margin hyperplane. The multi-class classification problem is reduced to a set of binary classification problems. Finally, the logistic regression (LR) classifier [61], also known as the maximum entropy classifier, models class probabilities with logistic functions of

linear combinations of features.

For each classifier, a small validation set was automatically generated in order to evaluate the classifier parameters. The sole parameter for the naïve Bayes classifier was the smoothing parameter, which was typically around 0.2. For the  
460 random forest classifier, four parameters were required, namely: features fraction, leaf size, number of trees, and distribution smoothing, which were set to  $1/2\sqrt{37}$ , 2, 100 and 0.5 respectively. This algorithm was implemented using the Intel Data Analytics Accelerations Library (DAAL) [63]. The gradient boosted trees approach requires numerous parameters, including the boosting method.  
465 This is based on the gradient, the maximum number of training rounds (50), the number of leaves (13), the learning rate (0.1), the maximum number of bins (255), the number of threads (20), the maximum depth (6), the leaf size (15), the feature fraction (1), and the bagging fraction (1) among others. For the SVM classifier, the following parameters were determined: kernel type (radial  
470 basis function), gamma scaling parameter (0.00725065), soft margin parameter (3), bias parameter (1), multiclass strategy (one versus one), and kernel cache size (100). Finally, the logistic regression classifier was optimized by means of the limited-memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) algorithm with a quadratic regularization term (0.001). Four metrics were employed to  
475 evaluate the performance of our system, namely: accuracy, precision, recall and F-measure. These metrics were chosen because of their performance and in order to compare our approach with those utilized in the benchmark databases. Since these metrics are well known and extensively used, we refer the reader to [64, 65] for more details. In addition, in some cases, we added the confusion  
480 matrix and the accuracy-rejection rate curve in order to further assert the performance of the system as well as its sensitivity with respect to the detection threshold probability. Here, the rejection rate refers to the classification probability of a given result: if this probability is below a certain threshold, the outcome of the classification process is considered undetermined and, consequently, not employed in evaluation of the performance metrics. Since the  
485 benchmark databases are relatively small, they are not really suitable for cross-

validation. Therefore, to evaluate the metric, we employed a bootstrapping or bagging technique. Bagging assumes that the dataset is representative of its real distribution. The training and validation sets are uniformly randomly sampled with replacement from the original dataset in order to train the classifiers. 490 The process was repeated ten times. Accuracy, precision, recall and F-measure correspond to the mean of these ten iterations.

Whenever possible, the classifiers were implemented on the GPU. The calculations were performed on a workstation with two Xeon processors with 40 495 cores, 64 GB of RAM and a NVIDIA Quadro GP-100 GPU with 3584 CUDA cores and 16 GB of memory.

### 6.2.1. *Experimental results for the TOSCA and SHREC11 Watertight Databases*

The *TSM* distance between each pair of tessellated models was evaluated 500 for the first six neighborhoods. These distances form the metric which must be learned. For each neighborhood order and for each classifier: accuracy, precision, recall, F-measure, confusion matrix, and accuracy-rejection rate curve were determined. Only the results associated with the three best classifiers are reported in Table 5 as these results are substantially better than the others.

505 For the second neighborhood order, the best results were obtained with the logistic regression classifier, while, for the first and the last four neighborhood orders, the best results were obtained with either the random forest classifier or the gradient boosted trees classifier. For the best classifiers, the lowest accuracy was 76.35% while the highest accuracy was 88.51%. Both were obtained with 510 the first neighborhood order using the gradient boosted trees classifier.

The accuracy-rejection rate curve and the confusion matrix are reported for the first neighborhood order in Figures 3 and 4 respectively. This accuracy-rejection rate curve clearly demonstrates that an accuracy of 95% may be easily achieved just by imposing a rejection rate of 0.1. The confusion matrix (Figure 515 4) further demonstrates the performance of our approach.



$N_k$	Accuracy			Precision			Recall			F-measure		
	GBT	RF	LR	GBT	RF	LR	GBT	RF	LR	GBT	RF	LR
1	<b>88.51</b>	83.78	85.81	<b>91.80</b>	85.12	88.34	<b>89.64</b>	80.41	87.41	<b>0.90</b>	0.80	0.86
2	71.62	79.05	<b>79.73</b>	72.31	<b>81.70</b>	81.60	74.40	80.41	<b>82.04</b>	0.72	0.80	<b>0.81</b>
3	<b>81.76</b>	79.73	77.27	<b>85.39</b>	79.87	77.41	<b>81.47</b>	78.50	77.52	<b>0.82</b>	0.78	0.76
4	75.00	<b>76.35</b>	61.49	77.35	<b>78.98</b>	68.07	75.40	<b>76.50</b>	64.26	0.74	<b>0.76</b>	0.62
5	<b>77.70</b>	72.30	62.21	<b>81.04</b>	74.29	66.06	<b>76.75</b>	71.10	68.20	<b>0.76</b>	0.70	0.68
6	<b>80.41</b>	79.05	62.21	<b>83.34</b>	80.18	66.06	<b>79.94</b>	78.96	68.20	<b>0.80.41</b>	0.78	0.68

Table 5: accuracy, precision, recall and F-measure obtained with the gradient boosted trees (GBT), the random forest (RF) and the logistic regression (LR) classifiers for the TOSCA Database.

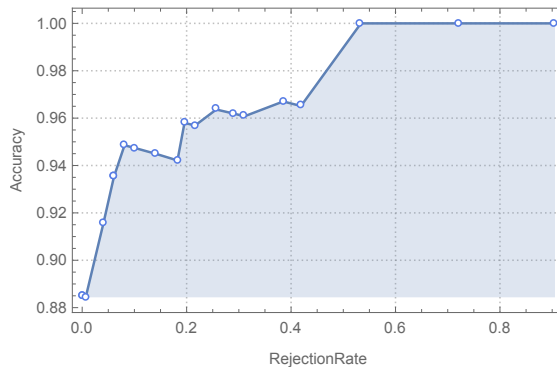


Figure 3: Accuracy-rejection rate curve for the first neighborhood order  $N_{k=1}$  for the gradient boosted trees classifier.

We also compared our method *TSM* with four other SHREC benchmark algorithms, namely CAM, GeodesicD2, DSR and RSH. Table 6 compares the precision reported by these approaches with the precision achieved by our method for the first neighborhood order with the gradient boosted trees classifier. Our approach clearly outperforms the others with a precision of 91.80% as opposed to a maximum of 30% for the four other approaches.

In addition, we compared our approach for all neighborhood orders with the TD, Shape-DNA and SRCP-TD methods in terms of F-measure. The results are reported in Table 7. Once more, our approach outperformed the others

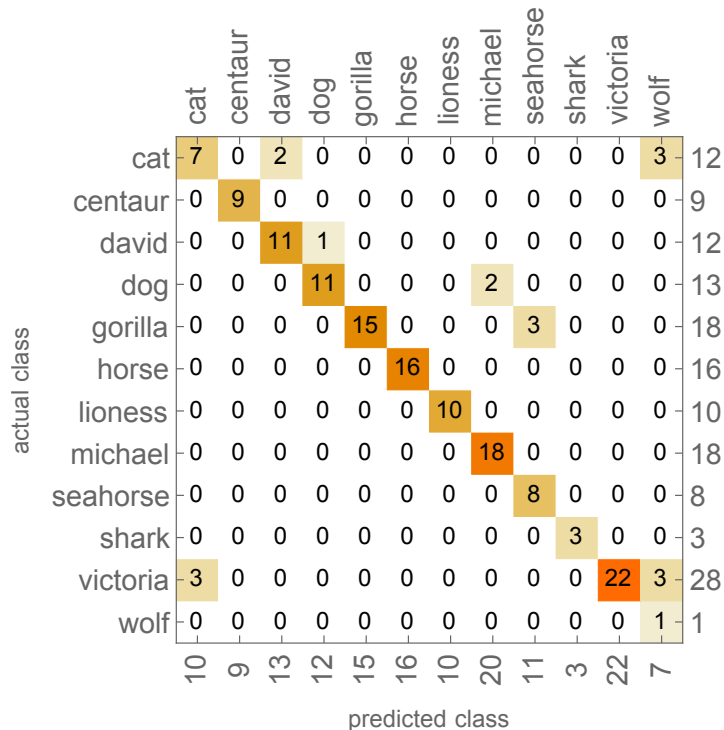


Figure 4: Confusion matrix for the first neighborhood order  $N_{k=1}$  for the gradient boosted trees classifier.

Method	Precision (%)	Recall (%)
$TSM, N_{k=1}, \text{GBT}$	<b>91.80</b>	<b>89.64</b>
CAM	30	89.64
Geodesic2D	26	89.64
DSR	24	89.64
RSH	21	89.64

Table 6: Comparison of our method  $TSM$  (first neighborhood order  $N_{k=1}$ ) in terms of precision with the CAM, Geodesic2D, DSR and RSH approaches for the TOSCA Database.

irrespective of the neighborhood order considered.

Finally, we report the results obtained with the SHREC11 Watertight Database. The experimental methodology was the same as that used for TOSCA. The best

Method	$N_k$	Classifier	F-measure
<i>TSM</i>	1	GBT	<b>0.90</b>
<i>TSM</i>	2	LR	<b>0.81</b>
<i>TSM</i>	3	GBT	<b>0.82</b>
<i>TSM</i>	4	RF	<b>0.76</b>
<i>TSM</i>	5	GBT	<b>0.76</b>
<i>TSM</i>	6	GBT	<b>0.80</b>
TD	N/A	N/A	0.67
Shape-DNA	N/A	N/A	0.45
SRCP-TD	N/A	N/A	0.44

Table 7: F-measure for the best classifier associated with a given neighborhood order compared with the F-measure obtained with the TD, Shape-DNA and SRCP-TD algorithms for the TOSCA Database.

530 results in terms of accuracy, for neighborhood orders two and six, were 65.80% and 69.16%, respectively; these were obtained with the random forest classifier.

### 6.2.2. *Experimental results for the TOSCA Database with respect to re-meshing*

We investigated the robustness of our approach *TSM* with respect to mesh reduction and re-meshing. This is of paramount importance since our method is based on the mesh or graph associated with the 3D models. The TOSCA Database [40, 41] was employed for the evaluation. The number of triangles was reduced by 10% and 20% in order to generate the TOSCA\_90 and TOSCA\_80 Databases respectively. The triangular reduction was realized with quadratic edge collapse decimation [66], which uses iterative contractions of vertex pairs to simplify the model and maintains surface error approximations using quadric matrices. By contracting arbitrary vertex pairs (not just edges), the algorithm is able to join unconnected regions of models. This may facilitate far better approximation, both visually and with respect to geometric error. The results we evaluated in terms of accuracy, precision, recall and F-measure for the TOSCA\_80 and TOSCA\_90 Databases are reported in Table 8.

545 Mesh reduction and re-meshing have a direct incidence on our approach since

$N_k$	Classifier		Accuracy (%)		Precision (%)		Recall (%)		F-measure	
	<b>T80</b>	<b>T90</b>	<b>T80</b>	<b>T90</b>	<b>T80</b>	<b>T90</b>	<b>T80</b>	<b>T90</b>	<b>T80</b>	<b>T90</b>
1	RF	RF	84.45	84.46	86.97	87.44	84.29	85.44	0.84	0.85
2	GBT	GBT	71.62	77.70	75.20	78.00	72.50	78.26	71.49	0.78
3	RF	GBT	71.62	73.65	73.50	76.85	74.09	75.29	0.73	0.75
4	RF	RF	79.73	75.00	81.97	78.32	80.95	77.08	0.80	0.76
5	GBT	RF	77.70	76.35	80.51	77.34	78.77	77.82	0.79	0.76
6	GBT	RF	74.32	73.65	80.82	74.74	75.59	73.06	0.76	0.73

Table 8: *TSM* accuracy, precision, recall and F-measure obtained with the gradient boosted trees (GBT) and the random forest (RF) classifiers for  $N_{k=1\dots 6}$  for the TOSCA.80 (T80) and the TOSCA.90 (T90) Databases.

the latter is graph-based. Nevertheless, *TSM* is based on an approximation of Graph Edit Distance which is fault-tolerant to noise and distortion. Furthermore, our approach uses a set of descriptors which are invariant or at least  
550 oblivious under the most common geometrical deformations. As a result, *TSM* is robust with respect to mesh reduction and re-meshing. Despite the fact that the triangular reduction was relatively great (10% to 20%), the algorithm displayed a surprisingly high resilience to mesh reduction: accuracy was as high as 84.5% for the first neighborhood order for both a 10% and 20% mesh reduction  
555 as opposed to 88.51% without mesh reduction. These results were all obtained with the random forest classifier.

Our experimentation with the TOSCA, the SHREC11 watertight and the mesh-reduced TOSCA databases, as described earlier, reveals the performances and robustness of our approach.

560 Indeed, we obtained excellent results in terms of accuracy, precision, recall and F-measure for the TOSCA and the SHREC11 watertight databases. Our predicted time complexity was systematically confirmed by our experimentations. Our method outperforms CAM, GeodesicD2, DSR and RSH in terms of accuracy, precision and recall for the TOSCA database. The same remarks  
565 apply when our approach is compared to other benchmark methods in terms of F-measure.

## 7. Conclusions

In this paper, we presented a new matching algorithm for addressing the problem of comparing deformable 3D objects represented by graphs (triangular tessellations). The proposed approach is based on a new decomposition of triangular tessellations into triangle-stars. The resulting triangle-stars are used to determine the distance between triangular tessellations using the Hungarian algorithm. The proposed algorithm ensures a minimum number of disjoint triangle-stars, offers a better dissimilarity by covering a larger neighborhood in triangle-stars and uses a set of descriptors which are invariant or at least oblivious under the most common deformations. The proposed approach is based on an approximation of Graph Edit Distance, which is fault-tolerant to noise and distortion, making our approach suitable for comparing deformable objects. Classification is performed using supervised machine learning techniques. Our approach defines a metric space using graph embedding and graph kernel techniques. We proved that the proposed distance  $TSM$  is a pseudo-metric. Our experimental results, as obtained from various benchmark databases for deformable shapes (TOSCA and SHREC11), confirm the performances and the accuracy of our algorithm. In a near future, we plan to enrich the triangle-stars description while reducing the time complexity and improving the performances of the proposed graph matching algorithm. We also plan to combine our approach with deep learning.

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