Towards a metric for computing similarity of restricted non-rigid objects in real time

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***Abstract*—We propose an approach towards measuring the similarity of restricted deformable objects using three-dimensional point clouds of them. Basically, given the point clouds of the object in the ideal and deformed postures, object part labeling is performed based on RGB to find a first segmentation of the object cloud in parts. Then two methods are tested for measuring similarity of each partial clouds set, with verification of their precision and time: the computation of Mahalanobis distances and of the Hausdorff distances of the point clouds, the last after registration and alignment of them. Experimental results show a faster execution time of the Mahalanobis metric, in despite of its lower precision in similarity estimation. Several applications in computer graphics and virtual reality can rely on such result in order to determine levels of deformation of articulated or restricted deformable objects.**

I. Introduction

There is a variety of applications in the research areas of Computer Graphics and Vision that have as one of their steps the determination of similarity between objects representations [1]. Examples of such approaches can be non-rigid shape matching [2], video similarity [3], 3D reconstruction [4], 2D and 3D object recognition and retrieval [5]–[8] and SLAM (Simultaneous Localization and Mapping). In general, objects can suffer rigid or deformable (non-rigid) transformations and they can be described by way of representative data structures of the shape of their surfaces. For example they can be described by polygonal meshes or triangles, or, more recently, represented by 3D Point Clouds. The latter is a representation that, although geometrically is the most elementary one in Computer Graphics, because it uses the primitive point, has been most used recently [9].

In some of the mentioned applications, regardless of the representation issue, it must be performed some process or algorithm in real time. For example, in the case of Robotics, for the recognition of objects it is required to use a similarity metric that efficiently meets the real-time requirement. On another example used in this work as our main motivation, if one seeks to find whether a seated person is in the right posture and to send him a signal for non correct posture, the real-time (on-line) issue appears again. So in this research, our visioned application is to determine whether a human posture gets degraded over time in relation to an ideal (supposedly correct), initial posture, due to human accommodation or fatigue. For this purpose, we consider that the human body is assumed as a strictly non rigid object and analyze its parts as restricted deformable objects, separately. Towards solving this practical problem, we propose an approach to estimate a similarity measure between objects represented by point clouds. Nonetheless, this approach can be applied on other similar problems for finding similarity between clouds.

The determination of the human pose (positioning plus orientation of all body parts) and a measure of similarity are the key techniques to be applied in order to solve the problem. We consider that the processing must be in real time (and on-line) and that the human parts, although deformable, do not suffer severe or considerable deformations (thus the term restricted deformation). That is, we deal with objects with a certain control of the rigidity, what we call as restricted deformable objects. Also, let's consider that the whole object can be segmented in parts and that each part can have a related counterpart in the object representation, on the ideal posture. So it can be measured whether it is similar (regardless a rigid body transformation) to that part. Using RGB and depth data, a segmentation of the global representation is done, obtaining several smaller point clouds, over which two similarity metrics or distances (Hausdorff and Mahalanobis) are experimented and verified to work in practice. Our experimental results have shown that the Mahalanobis metric, has a smaller execution time than the Hausdorff metric. However, the Hausdorff has a better precision in the similarity estimation in some cases as expected, besides consuming more time. Several applications in computer graphics and vision can rely on such approach in order to determine the levels of deformation of similar articulated or restricted deformable objects.

In this way, in the first part of this article analyzes some similarity metrics for point clouds obtained of non-rigid objects by way of using RGB-D sensors, with some background theory and methodology. In the second part, related works are presented, then the method devised is introduced in detail. Lately, an experimental results analysis is done, and the conclusions are presented.

II. Background and Methods

Certain type of non-rigid objects, as the human body, may have some changes in their size and shape due to internal stresses produced by one or more forces applied on it. The

[1]This work is related to a Master's Thesis

modeling and analysis of the characteristics of these objects have been the tasks approached in several applications of Computer Graphics. Formally, objects can suffer rigid body transformations such as rotation and translation only, as well as non rigid: elastic, topological, scale, data loss and inelastic [5]. In the analysis of similarity of non-rigid objects is necessary to consider these two groups of transformations.

Nonetheless, it is necessary to understand the concept of distance, as the Euclidean distance that is just one special case of a family of functions, the metric measures, or simply distances (in mathematics, distances and metrics can be considered as synonyms [10]). Many metrics can be considered for data analysis purposes (similarity is our case). Formally, any function d_{jk}, which satisfies the following conditions (metric axioms) for all points, is considered a metric [10]:

1) If two points coincide, that is $j = k$, then it follows that $d_{jk} = 0$ (d_{jk} is zero if and only if $j = k$).
2) If the two points differ, that is $j \neq k$, then $d_{jk} > 0$.
3) According to the symmetry axiom $d_{jk} = d_{kj}$ (that is, the direction of measurement is not important here).

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A. Mahalanobis distance

The Mahalanobis distance between a set of values with mean $\mu = (\mu_1, \mu_2, \mu_3, \ldots, \mu_p)^T$ and covariance matrix S for a multivariate vector $x = (x_1, x_2, x_3, \ldots, x_p)^T$ is defined as [11]:

$$D_M(x) = \sqrt{(x-\mu)^T S^{-1} (x-\mu)}. \tag{1}$$

This metric represents the covariance distance of all data. The performance of the Mahalanobis distance is usually better than that of the Euclidean Distance because it considers the size of the pattern characteristics parameters and the correlation of characters. It is an efficient way to calculate the similarity of two unknown samples and it has three important properties: translation invariability, rotation invariability and affine invariability [12].

B. Hausdorff distance

Considering two finite points sets $A = a_1, a_2, ..., a_n$ and $B = b_1, b_2, ..., b_m$, the Hausdorff distance is represented as [13]:

$$H(A, B) = max(h(A, B), h(B, A)) \tag{2}$$

where

$$h(A, B) = max_{a \in A}(min_{b \in B} d(a, b)) \tag{3}$$

and

$$h(B, A) = max_{b \in B}(min_{a \in A} d(a, b)) \tag{4}$$

Where $d(a, b)$ is a norm calculated on the points of A and B (usually L_2 or Euclidean norm). The Hausdorff distance has been investigated and also used here because it is simple and insensitive to changes of RGB(D) data characteristics, regardless severe deformations on the data. That is, it is insensitive to any restricted affine transformation as defined here, as it refers to internal distance measures that are not affected by this kind of transformations. In our case, as we put a limit on the deformations, they can be also dealt with the Hausdorff distance, with some small degradation that do not affect performance. In fact, we show results verifying that, later on the experiments Section.

III. Related Works

Researches with human body posture determination, classification and recognition [14]–[16] have received a great deal of attention recently mainly for applications as human behavior analysis [17], [18], 3D human body shape determination [14] and human action recognition [16], [19].

Measuring similarity between elements, objects, shapes or other entities that can be represented in a computer as a data structure is an issue that appear in several works in the literature [20], [21]. If data can be represented in form of discrete signals, numbers, or values, approaches as correlation or correntropy [22] can be used to determine the matching between elements in a series of samples. In computer graphics, where all sort of data structures can be used to model objects, often arises some similarity problem, in 2D, 3D, points, lines, polygons, volumes, or shapes. More specifically related to measuring human body similarity, which is this work subject, from the literature we notice that the study of the human body within the areas of Computer Graphics and Vision is the focus of a very broad set of researches [2], [5], [14]–[16], [23]–[25]. A nice survey on the techniques for 3D pose estimation of human body can be found in the work of Sarafianos [19].

The Mahalanobis and Hausdorff distances have also been used in the context of object recognition in images (2D) [26], [27] and shape matching [25], [28]. Hausdorff distance application to cloud points is also reported in the literature [13], but not for the same problem and with the approach as proposed here.

There are several applications where the similarity problem appears. One of these applications is incorrect posture detection (as mentioned above) that we start working on recently [29]. Human part labeling [30] and human motion analysis and action recognition also appears as a well studied research problem [17]. These techniques are applied in this work to segment the acquired cloud of points in several ones, one for each part of the human body. Then Hausdorff and Mahalanobis distances are applied and their performance measured for this particular problem, as described next.

IV. The proposed approach

In general, the human body can be studied as an articulated system that is composed of segments connected by joints [18], [19]. In the present work, each segment is further understood as a restricted deformable object. This means that in spite of being deformable, one has certain limits on the deformation that can be applied to any body part. Certain class of deformations as some large elastic transformation are not allowed, for example. With this in mind, we start building our approach, next.

A. 3D body parts labeling

Previous to computing the similarity between a certain part of a human body (before and after undergoing a certain transformation), it is necessary to obtain an isolated representation of each part. In this case we chose to represent these parts with point clouds, which that can be obtained as raw data acquired by some 3D sensor, as the stereo ZED camera [31] or the MS Kinect v1 . In order to segment the human body (eliminate all the objects of the scene except the human body) and to labeling of the parts we use the algorithm proposed by Carraro [32], with some modification in order to eliminate outliers and reducing errors.

So, here it is proposed an improvement to Buys' body pose detector [33], by adding a preliminary people detection phase for background removal as introduced by Munaro [34]. This helps elimination of some outliers. Then a segmentation of the remaining (body) is performed. To obtain a point cloud for each of a body part, it is firstly considered the RGB value of a color assigned to the segmented image and a labeling of the human body RGB image is performed as shown in the Figure 2a. The algorithm selects all the pixels with this color and through Equations 5 and 6 together with the values of the depth map (Figure 1b) the coordinates X and Y of the required part are re-projected.

$$u = f\frac{X}{Z} + Cx \qquad v = f\frac{Y}{Z} + Cy \tag{5}$$

$$X = \frac{u - Cx}{f}Z \qquad Y = \frac{v - Cy}{f}Z \tag{6}$$

(a) (b)

Figure 1. (a) RGB image with the segmented and labeled human body and (b) Depth map generated or acquired by some process.

In the process of labeling and body part estimation some pixels of the RGB image (Figure 1a) that do not correspond to a certain part are assigned, so with the wrong color. This implies that in the projected points cloud there are outliers. To eliminate them we perform a filtering process considering a certain number of points that should exist in a sphere of some empirically determined radius, towards the centroid of the cloud

B. Mahalanobis distance computation

Considering the mathematical expression of Equation 1 we calculate the Mahalanobis distance of each point using coordinates X, Y, Z of the point clouds. In this case the mean corresponds to centroid of the cloud. The number of calculated distances varies according to the size of the cloud. A representative value of the point cloud of a particular part is developed here based on a summation.

C. Hausdorff distance computation

In order to obtain a value that allows to compare two clouds of points of non rigid objects, it is calculated the distance of Hausdorff expressed by Equation 2. Notice that if two clouds of points represent the same object (part) with the same spatial location, this distance would be zero (or close to). This value change when either one or two objects have undergone a rigid or not rigid transformation. This is attributed to the fact that the Hausdorff distance is not invariant to changes in scale, rotation and translation. So, the body parts should be registered and aligned previous to computing it.

That is why, for our analysis of non-rigid objects, we propose to perform a registration and alignment of the points clouds before computing the Hausdorff distance, so the variations generated in the case of presenting rigid transformations are inconsiderate This allows that the values obtained with this metric indicate clearly the changes between the objects due to non-rigid transformations to later determinate any degree of similarity between them.

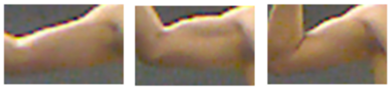
The registration and alignment of two points clouds that can represent an object before and after a deformation respectively, is performed with the Iterative Point Cloud algorithm proposed by Holz [35].

D. Similarity of clouds

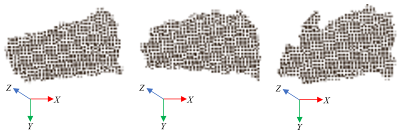
The similarity between two deformable objects as proposed in this work is represented by a percentage value, which is determined as a function of the results obtained when computing Hausdorff or Mahalanobis distances in each point clouds of them. Here we use several point clouds of body parts. We try to analyze similarity before and after suffering a rigid and non rigid transformation. Notice that as mentioned above the non rigid objects have a maximum limit of deformation, this posture is taken as reference of null similarity (totally different). For this reason it is included a third point cloud of the object that represents this position. Figure 2 shows three non rigid deformations of the right arm and their points clouds (Figure 2b). The first two columns correspond to the objects that we want to estimate the similarity and the third is the maximum deformation of it that is possible to perform.

To calculate similarity based on the distances of Hausdorff, this metric is first determined between the first point clouds (that can be considered without deformation) and the cloud that represents the maximum deformation of the object. This value represents a similarity of 0% (that means totally different). After, this computation is repeated between the two clouds of interest to later calculate trough proportionality the desired percentage of similarity.

In the case of the similarity analysis based on Mahalanobis distance, it was necessary to calculate these distances for



(a)



(b)

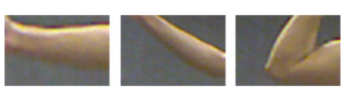
Figure 2. (a) RGB images of the arm in ideal posture (left), with some deformation (middle) and with most deformation possible (right) and (b) point clouds of them (already segmented).

the three point clouds considered in the process as described above (Figure 2). When varying the level of deformation the same object, we noticed that the distances of Mahalanobis of their respective clouds also varies. To get a similarity value, it is taken as reference of maximum variation (0% similar) to the absolute difference between the distance of the first analyzed cloud and the third cloud. If the difference of the Mahalanobis distances between the two clouds whose similarity is required results zero, the object does not have a non rigid transformation. This means that the two clouds can represent the same object, they may or may not be in a different spatial location that is not detected by Mahalanobis distance. Notice Mahalanobis is insensitive to rigid body transformations.

V. Experiments and results

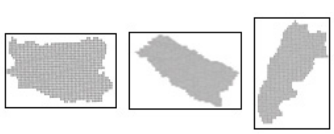
In order to verify the previous approaches, we have performed some experiments with a human body, from which the input data is taken using MS Kinect v1. (see Figure 2).

The points clouds shown in the Figure 2b were obtained from the RGB data of the Figure 2a and the depth maps. One of the clouds defines the ideal posture (left) and the others are deformed postures (the right one has the largest deformation possible). To get these points clouds the parts of the human body were segmented and filtered.



(a) Original RGB images

(b) Segmented RGB images



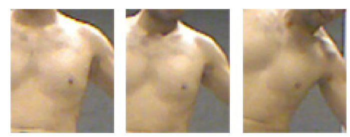
(c) Points clouds

Figure 3. Images of a forearm and their respective points clouds

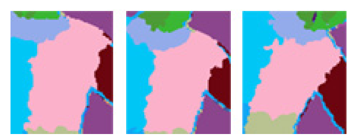
In addition to using the arm point clouds shown in Figure 2, some other parts were chosen in order to present a better analysis of the results.These parts (including the arm) are: right hand, right forearm, neck, right and left chest parts.

Figure 3 shows the original RGB images (Figure 3a), the RGB segmented images using Buys' method (Figure 3b) and the corresponding clouds of the right forearm (Figure 3c). These points clouds are the inputs the similarity determination process that use Mahalanobis and Hausdorff distances. Before computing Hausdorff distance it is necessary to make a previous step of register the clouds because this metric is sensitive to the rigid body transformations.

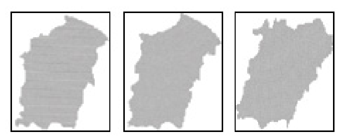
Figure 4 shows the original RGB images, the RGB segmented images and the points clouds employed in the analysis of left chest part. For the analysis of the right part of the chest, the chosen postures are similar to those considered for the left side.



(a) Original RGB images



(b) Segmented RGB images



(c) Points clouds

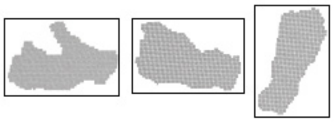
Figure 4. Images of the chest left part and their respective points clouds

The right hand analysis is developed with the data shown in Figure 5, it is noticed that the results of the Hausdorff distance don't show correctly the level of deformation applied to it. The result of the Mahalanobis distance has a better accuracy, this is attributed to the deformation degree of the ideal posture and the maximum deformation clouds are greater compared to the other body parts analyzed, also this is the reason for the substantial variation in the results obtained with Mahalanobis and Hausdorff distances. When the deformations are larger, the results provided by the Hausdorff analysis are not reliable, mainly because registration and alignment processes are done considering non-rigid objects in this case.

Figure 6 shows the RGB images and points clouds used in the analysis of the neck. Here both distances were coherent, giving the highest scores of similarity. This means that it does not happen a substantial deformation in the neck postures, even with a certain degree of rotation seen in the third image of the Figure 6a.

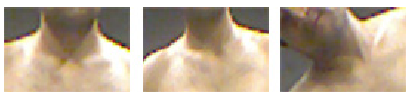
(a) Original RGB images

(b) Segmented RGB images



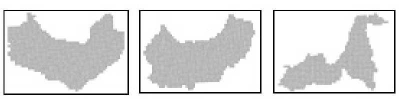
(c) Points clouds

Figure 5. Images of a hand and their respective points clouds



(a) Original RGB images

(b) Segmented RGB images



(c) Points clouds

Figure 6. Images of a neck and their respective points clouds

Table I shows data comparison obtained from the similarity analysis of some parts obtained using the Hausdorff and Mahalanobis distances. As higher is the number, more similar are the parts. Notice that Hausdorff has the minimum similarity for the hand (21.9%) and the maximum for the neck (68.64%). The last is not as deformable as the hand. Mahalanobis has the minimum of similarity for the left chest (39.55%) and the maximum for the neck (88.52%). The Mahalanobis metric worked best in the analysis of the right hand, this occurs because it does not need registered and aligned clouds.

Table I
SIMILARITY'S PERCENTAGES OF BODY PARTS

Body part	**Mahalanobis Dist (%)**	**Hausdorff Dist (%)**
Right hand	75.68	21.9
Right forearm	51.85	30.78
Right arm	64.88	24.87
Neck	88.52	68.64
Right chest	48.47	27.43
Left chest	39.55	26.48

Table II
COMPUTATION TIMES OF SIMILARITY'S PERCENTAGES OF BODY PARTS

Body part	Point cloud size	Mahalanobis time (ms)	Hausdorff time (ms)
Right hand	1184	45	376
Right forearm	1127	40	241
Right arm	1762	94	371
Neck	1086	37	224
Right chest	4672	637	990
Left chest	3977	464	826

Table II shows the computation times of similarity's percentages of body parts. Notice the time for Hausdorff is substantially bigger than that for Mahalanobis, almost one second in some cases (right chest for example), even reducing the amount of points with segmentation. For this reason, it can not be applied to real time applications.

In the case of the forearm, it was not considered a high level of deformation. The results obtained for similarity analysis are similar for both distances. However, it is noticed a large difference in the processing time (of 201 ms). Notice that further improvements can be done on this issue for allowing its use in real time applications.

VI. Conclusion

A complete approach is proposed towards measuring the similarity of restricted deformable objects using three-dimensional point clouds of them. For that, given the point clouds and RGB of the object in the ideal and deformed postures, a segmentation is performed based on RGB to find a the object part labeling, with which clouds of points are created. These clouds are used as input for two similarity measures, the Mahalanobis metric and the Hausdorff metric, this one after registration and alignment of pairs of point clouds of each part.

The practical application visioned is the problem to determine whether a human ideal posture gets degraded over time, based on point clouds and RGB acquired by a depth sensor (ex. MS Kinect or the ZED camera). Using real data acquired from a subject, the experimental results have shown that the Mahalanobis metric, has a smaller execution time than the Hausdorff metric. However, the Hausdorff has a better efficacy in the similarity estimation, as expected, besides not allowing its application in real time.

In conclusion this proposed approach, based on Mahalanobis, can be applied as a solution for the problem of determining whether a human ideal posture gets degraded over time. Other applications in computer graphics and vision can rely on such approach in order to determine the deformation level of similar articulated or restricted deformable objects or else similarity between objects represented as point clouds.

Acknowledgment

The authors would like to thank to the CAPES and CNPq, Brazilian Sponsoring Agencies for Higher Education and Research for the research grants of Elizabeth Cabrera (CAPES), Luis Ortiz (CAPES) and Luiz Gonçalves (CNPq).

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