A Privacy Algorithm for 3D Human Body Scans

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Abstract. In this paper, we explore a privacy algorithm that can detect human private parts in a 3D scan dataset. The intrinsic human proportions are applied to reduce the search space an order of magnitude. A feature shape template is constructed to fit the model data points using Radial Basis Functions in a non-linear regression. The feature is then detected using the relative measurements of the height and area factors. The method is tested on 100 datasets from CAESER database.

1. Introduction

The rapidly growing market of three-dimensional holographic imaging systems has created significant interest in possible security applications. The devices operate using a millimeter wave transceiver to reflect the signal off the human body and any objects carried on it. Unlike current metal detectors, the system can detect other threats or contraband, including metal, plastic, liquids, drugs and ceramic weapons hidden under clothing. The technology has also been used to create body measurements for custom-fit clothing. The holographic imager creates a high-resolution 3-D scan of a body, allowing shops to provide tailored measurements to designers or provide recommendations on best-fit clothing. However, the high resolution scanned images reveal human body details that have raised privacy concerns due to the fact that the scanner produces an almost naked image of the subject. Airport and transport officials in several countries are refusing to run a test trial with the scanners until a more suitable way to conceal certain parts of human body is found.

The scanner creates a three-dimensional point cloud (voxels) around the human body. Since the millimeter wave signal can not penetrate the skin, a three-dimensional human surface can be found. Furthermore, since the typical pose of a subject is standing, we can segment the 3-D dataset into 2-D contours, which reduces the amount of data processing significantly. The goal of this study is to develop a method that can efficiently find and conceal the private parts of a human.

2. Relevant Studies

From a computer vision point of view, detecting features from 3D body scan data is nontrivial because human bodies are flexible and diversified. Function fitting has been used for extracting special landmarks, e.g. ankle joints, from 3D body scan data [1,2], similar to the method for extracting special points on terrain [5]. Curvature calculation is also introduced from other fields such as the sequence dependent DNA curvature [3]. These curvature calculation use methods such as chain code [7] circle fit, ratio of end to end distance to contour length, ratio of moments of inertia, and cumulative and successive bending angles. Curvature values are calculated from the data by fitting a quadratic surface over a square window and calculating directional derivatives of this surface. Sensitivity to the data noise is a major problem in both function fitting and curvature calculation methods because typical 3D scan data contain loud noises. Template matching appears to be a promising method because it is invariant to the coordinate system [1,2]. However, how to define a template and where to match the template is challenging.

In summary, there are two major obstacles in this study: robustness and speed. Many machine learning algorithms are coordinate-dependent and limited by the training data space. Some algorithms only work within small bounding boxes that do not warrant an acceptable performance. For example, if a feature detection algorithm takes one hour to process, then it is not useful for a security screening system. In this paper, we present a fast and robust algorithm for privacy protection.

3. Intrinsic Proportions

Our first step is to reduce the search space of the 3D body scans. We start by dividing the 3D data points into 2D slices. The points are 'snapped' to the nearest planes enabling us to convert a 3D problem to 2D. In this study, we assume that body features can be detected from the contours on the cutting planes. Examining each slice from top to bottom is rather an expensive process. Here we present a novel approach to reduce the search space by making use of intrinsic proportions. It is a relative measurement that uses an object in the scene to measure other objects [15].

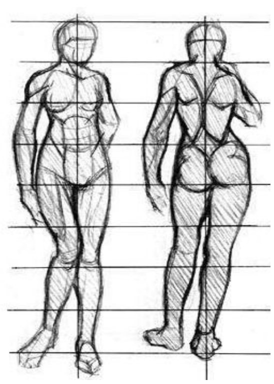

Fig. 1 Body height measured by head

Intrinsic proportion measurements have been used in architecture and art for thousands years. Roman architect Vitruvius said that the proportions of a building should correspond to those of a person, and laid down what he considered to be the relative measurements of an ideal human. Similarly in art, the proportions of the human body in a statue or painting have a direct effect on the creation of the human figure. Artists use analogous measurements that are invariant to coordinate systems. For example, using head to measure the height and width of a human body, and using an eye to measure the height and width of a face. Figure 1 shows a sample of the vertical proportion in a typical art book. Based on our observations from 100 3D scan data sets of adults from 16 to 65 years old, including subjects from North America, Europe and Asia, we found that the length of one and a half head units from the bottom of the head is enough to cover the chest area. In addition, the chest width is about three heads wide. Figure 2 shows an output from the intrinsic proportion calculation based on the sample from CARSER database.

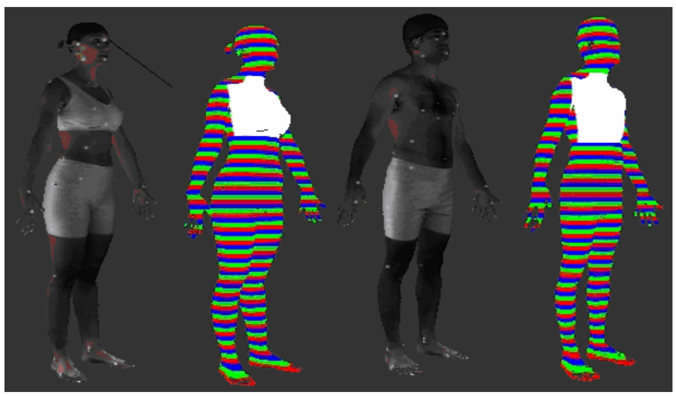

Fig. 2 Detected chest in white

We found that intrinsic proportion method can reduce the search space by an order of magnitude. In addition, it reduces the risk of the local optima while searching the whole body. Although this method is not fool-proof as each human is different, it is a reasonable place to start a search.

4. Template Matching

Template matching is image registration that matches a surface, of which all relevant information is known, to a template onto another surface. The matching of the two surfaces is driven by a similarity function. We need to solve two problems for applying template matching on the regions of interest. First, a suitable template had to be created. Second, a similarity function had to be selected, so that a minimization algorithm can align the template onto the region of interest. For each plane of the scan data, the back of the body contour can be removed. By assign the X-axis to between the two points with the longest distance, we can obtain the front part of the body contour. We then use three radial basis functions to configure the template for female breast pattern.

$$Y = \sum_{i=1}^{3} a_i * \exp(-(n - s_i)^2) \qquad (1)$$

where, $a = a_1 = a_2$, $b = a_3$, $s = s_1 = s_2$, and $s_3 = 0$.

We use non-linear regression on the variables *a*, *b*, and *s* to match the template with the scan data. Figure 3 shows the matching results for the female and male samples.

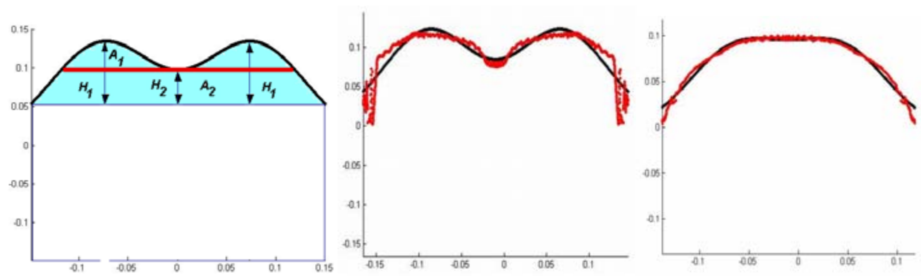

Fig. 3 Variable definitions for the breast template (left), matching results for the female sample (middle) and male sample (right). The solid black curves are the template contours. The red points are the 3D scan data.

5. Coordinate Invariant Measurements

Most shape descriptions depend on coordinate systems and viewpoint, meaning that the algorithm can only work within the training data space. Our shape invariant measurements are aimed to compute the shape properties from the ratio, rather than absolute values.
Template matching not only filters out noises but also describes the characteristics of a shape. We define the following similarity functions, which are invariant, to the coordinate system: height ratio and area ratio. The height ratio is defined as

$$H_r = \frac{H_1}{H_2} = \frac{Y_{mid/2}}{Y_{mid}} \qquad (2)$$

The area ratio is defined as the ratio of the area of curvature feature *(A_1)* to the total area *(A_2)* of the model by the following formula:

$$A_r = \frac{A_2}{A_1} \qquad (3)$$

where, $$A_2 = \int_l \sum_{i=1}^{3} a_i * \exp(-(x - s_i)^2) dx \qquad (4)$$

$$A_1 = \int_l (\sum_{i=1}^{3} a_i * \exp(-(x - s_i)^2) - c) dx \qquad (5)$$

$$c = \sum_{i=1}^{3} a_i * \exp(-(mid - s_i)^2) \qquad (6)$$

We used the Taylor series to find an appropriate approximation.

$$A_1 = \sum_{i=1}^{3} a_i * (1 - (x - s_i)^2 + \frac{(x - s_i)^4}{2!} + \frac{(x - s_i)^6}{3!} + \frac{(x - s_i)^8}{4!}) \qquad (7)$$

$$A_2 = \sum_{i=1}^{3} a_i * (1 - (x - s_i)^2 + \frac{(x - s_i)^4}{2!} + \frac{(x - s_i)^6}{3!} + \frac{(x - s_i)^8}{4!}) - c \qquad (8)$$

Another method utilizing the compactness of the polygon [27] was attempted. Due to the fact that Male models are in general larger and therefore have a longer border length it was determined that this method was not an effective feature differentiator as the area ratio method.

5. Results

We tested our algorithm with the subset of CAESER database that contains 50 males and 50 females ages 16-65, where 50 of them are North American with a black mix, 24 are Asian, and 26 are from the European survey from Italy and the Netherlands. We try to find the breast features from known female and male scan data samples. Figure 4 shows the test results. From the plot, we can see the distinguishable two groups for male (without the curvature feature) and female group (with the curvature feature). There is a 'dilemma' zone where some over-weight males do have the curvature features. However, the over-lapped zone is small, less than 8% of the total 100 samples.

Fig. 4 Chest feature detected

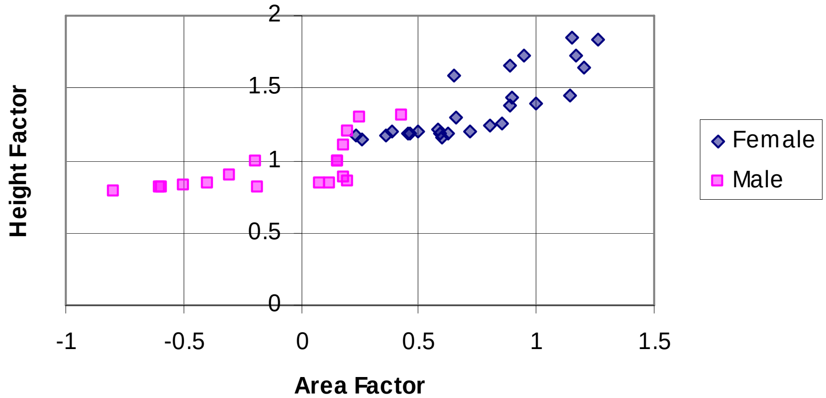

Fig. 5 Classification test results with male and female samples

After the area and height factors have been calculated we determine the feature area, as seen in Figure 5. Once we find the feature area, we reduce the polygon resolution so that the area is blurred. Figure 6 shows the results of the blurring effects.

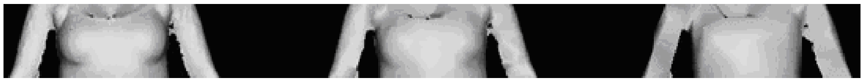

Fig. 6 Blurred surface rendering

6. Conclusions

In this paper, we explored the algorithm to recognize the body feature areas and blur them for protecting subject's privacy. Human intrinsic proportions are used to drastically reduce the search space and reduce the local optima. The feature template is defined with Radial Basis Functions whose parameters are determined by non-linear regression. Feature factors of the height and area are then used to recognize the curvature feature. The relative measurements are coordinate invariant. With non-linear regression method, the template matching is effective and convergent within given error range. We tested with 100 body scans from the CAESER database and found the algorithm can classify the male and female bodies based on the curvature features at the successful rate of over 90%.

Our future work includes the development of more robust coordinate invariant method to detect the predefined body features, the balanced algorithms both for protecting privacy and detecting concealed weapons. Ultimately, we will work with the real field data to fine tune the algorithms.

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