Surface Reconstruction from Point Cloud of Human Body by Clustering

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SUMMARY

This paper proposes a method in which the body surface is reconstructed from a point cloud (set of points) on the human body acquired by a device such as a laser range finder. The method constructs the surface appropriately for the human body by clustering the point cloud at body sections such as the chest and the upper arm. The clustering is performed as follows. A simple human model composed of cylinders, ellipsoidal columns, and hemispheres is assumed. The posture is estimated by matching the human body model to the point cloud data. Based on the estimated posture, the point cloud is assigned to body sections. Since the posture is inferred from the point cloud, the method is effective not only for an upright standing posture, but for point cloud data obtained from an arbitrary posture. Experiments were performed to apply the method to simulation data and measured data, and it was shown that a realistic surface could be reconstructed. The surface can be reconstructed for postures other than the upright standing posture. The effectiveness of the proposed method is thus verified. © 2006 Wiley Periodicals, Inc. Syst Comp Jpn, 37(11): 44–56, 2006; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/scj.20230

Key words: surface reconstruction; human body model; point cloud data; posture estimation.

1. Introduction

Efforts are being made to create computerized human models that reflect the shape features of the individual. This technique is becoming more important not only in entertainment, such as television and film, but also in fields such as the design of various human wearing apparel (clothing, etc.).

There are many methods of measuring the shape of the human body, such as the use of laser range finders and stereo vision systems. Whatever method is used in the measurement of the individual shape, the acquired data can generally be represented as the set of discrete 3D coordinates (point cloud data) of the body surface. To handle the acquired data in a unified way for the display of the human body and for the design of related products, a surface reconstruction method for the point cloud will be required.

There have been previous efforts to reconstruct the surface from the point cloud [1–4]. Although these methods consider a point cloud of arbitrary configuration, they are vulnerable to noise and absence of data. When the human body, with its complex shape, is measured, the acquired point cloud usually is missing data due to self-occlusion. If conventional methods are applied to such a point cloud to reconstruct the surface, some parts of the reconstructed surface, such as the armpits and crotch, fill a concave region, and points are likely to be missing, which will prevent the actual human body shape.

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In this study we consider point cloud data obtained by measuring the human body, and attempt to reconstruct the surface on the basis of structural features to prevent the generation of spurious surfaces between different body sections, as in the armpits and crotch. The human body can be divided into major body sections, namely, the head, the torso, the right and left upper arms, forearms, thighs, and lower legs and feet. If a surface is reconstructed for each body section, spurious surfaces filling the gaps between body sections are not generated. In order to reconstruct the surface for each body section, the point cloud data are clustered into body sections in the proposed method.

2D projection and a 2D Delaunay net are used in the surface reconstruction for each body section [5]. Except for the head, the hands, and the feet, which have complex shapes, each body section can be treated as a cylinder. The point cloud clustered into each body section is projected onto a second-order curved surface, such as a cylinder, and the points are connected by constructing a 2D Delaunay net on the projection surface. The connection relation is applied to the original point cloud and the surface of each body section is constructed. By aggregating the results, the surface of the whole body is reconstructed.

At present, the general procedure for measurement of the individual body shape is that the subject takes an upright standing posture. However, it should be noted that the muscles in the human body deform according to the posture, which produces complex changes in the surface shape. Consequently, it should be possible to reconstruct the surface from the data acquired from any posture. To allow the point cloud acquired from an arbitrary posture to be clustered into body sections, the posture must be estimated from the point cloud.

This paper is organized as follows. Section 2 describes a method in which volume data are constructed from the point cloud data and the posture is estimated by model matching. Section 3 describes the method of clustering the point cloud into body sections. Section 4 presents experimental results, and Section 5 gives conclusions.


The point cloud to be handled in this study does not contain information distinguishing the inside and outside of the human body in 3D space. Consequently, it is difficult to match the point cloud directly to the human body model. First, volume data are constructed from the point cloud data in order to distinguish the inside and outside of the body in the space [6]. By matching the human body model to the obtained volume data, the posture can be roughly estimated. The estimation accuracy of the posture is not high; the posture is estimated more precisely by fine adjustment using the point cloud data.

2.1. Human body model

The human body is divided into body sections, namely, the head, chest and waist, and the right and left upper arms, forearms, thighs, and lower legs. Each body section is represented by 3D elements, combining cylinders, hemispheres, and elliptic columns, and these elements are then used to construct the whole body model (Fig. 1). The cylinders and elliptic columns representing the respective body sections are connected at joints. The body sections can rotate around the joints. In order to determine the initial position in the posture estimation, a cylinder covering the chest and abdomen is created to represent the torso. The size of each body section is set in accordance with average values for adult males [7].

In order to estimate the position of the measurement target in terms of the center of gravity of the point cloud, the center of gravity of the human body model is defined in accordance with the center of gravity of the point cloud. Preliminary experiments have shown that the center of gravity of the point cloud data is almost always in the lower abdomen, regardless of the absence of data or of the posture of the measurement target. Consequently, the midpoint of the axis of the elliptic column representing the waist of the human body model is defined as the center of gravity of the human body model.

2.2. Construction of volume data (voxels)

The method of Matsuoka and colleagues [4] is used in the construction of the volume data. They determined the voxel size by calculating the density of the sparsest part of the point cloud. Using that voxel size, contour voxels are defined for the point cloud. By defining the part surrounded by the contour as inside voxels, volume data are constructed.

Fig. 1. Human body model.
In this method, however, the voxel size is greatly enlarged if the point cloud contains noise or defects. Thus, it is impossible to represent spacing, such as that between the chest and the upper arm, which makes it difficult to estimate the posture by matching. In this method, upper and lower limits are defined for the voxel size so that the constructed volume data will be consistent with the human shape. Figure 2 shows the volume data thus constructed.

When the voxel size is limited, it is impossible to construct contour voxels which cover the whole surface of the object. It is also impossible to determine the inside voxels precisely. Furthermore, for parts where most of the body section is missing, it may be that neither the contour voxels nor the inside voxels can be constructed. However, since the purpose of this method is to construct volume data which provide clues for matching, no problem arises if complete volume data are not constructed.

### 2.3. Matching between volume data and human body model

Matching of the human body model to the volume data constructed by the method described in Section 2.2 is next performed. The matching is performed successively from the chest, with a large volume, to the extremities (Fig. 3).

1. **Setting of initial position of human body model**

   First, an attempt is made to match the initial position of the body model to the point cloud data. The center of gravity of the point cloud data is aligned to the center of gravity of the human body model defined in Section 2.1. Then the torso, which has the largest volume in the human body model, is matched to the volume data constructed as described in Section 2.2, and the rough position and orientation of the human body are estimated.

2. **Estimation of position of body sections**

   After the above procedure, matching of the sections of the body model is attempted from the chest to the extremities, in the order of the chest, the right and left upper arms and forearms, and the thighs and lower legs.

   Based on the results of matching to the volume data, the points which are located within a certain distance from the surface of each section of the human body model, “model surface of section,” are extracted. Then, the positions and angles of the body sections (posture) are adjusted so that the square-sum of the distances from the model surface of section to the points is minimized. The Euclidean distance is used as the distance from the model surface of section to a point. The width and length of each section of the human body model are determined from statistical data, and may deviate from the actually measured values for the body sections. Consequently, the radii and lengths of the cylinders composing the sections of the human body model are adjusted by using the point cloud data.

   The radius is set as the average distance from the central axis of the model to the extracted point cloud. The
length is determined by estimating the ends of the body section. The end of the body section is estimated by locating the extracted points for which the distance from the central axis of the model falls below a preset threshold. If such a point cannot be found, it is judged that the end of the body section is not closed, and the length is not adjusted. In a posture with an extended arm, the end of the body section cannot be identified, but no problem arises, since this does not generate spurious surface in the surface reconstruction.

3. Clustering of Point Cloud and Surface Reconstruction

In order to reconstruct the surface, the point cloud is clustered into the body sections by using the human body model with the estimated posture. Let us consider the case in which the surface is reconstructed simply, by clustering into a given body section the points that are nearer than the threshold $T_d$ to the model surface of section. As a result, spurious surfaces are generated at parts such as the armpits, where multiple body sections are close to each other, but not connected in practice.

In the proposed method, clustering is further refined (Section 3.1) by using the distribution of the distance of the point cloud from the model surface of section to correct the results of clustering based on the threshold $T_d$. After this processing, points which are clustered into multiple body sections still remain. In the surface reconstruction, it is desirable that the point cloud be clustered uniquely into body sections except for the parts connecting body sections. Then, by utilizing neighborhood information, a single clustering destination is chosen for such points as far as possible (Section 3.2). Finally, using 2D projection and a 2D Delaunay net, the surface is reconstructed from the clustered point cloud of each body section.

In order to represent the position of each point in the point cloud, a coordinate system is defined as follows for each section of the human body model. We denote the component along the axis of the cylinder composing the body section as $h$, the distance from the cylinder surface as $r$, and the angle on the plane perpendicular to the axis of the cylinder as $\theta$ ($0 \leq \theta \leq 2\pi$). Then the 3D cylindrical coordinate system $(r, \theta, h)$ is used. The direction of the angle $\theta$ is set arbitrarily.

3.1. Clustering based on distance distribution

The body section to be measured is not a cylinder or elliptical column in practice. Consequently, there are fluctuations in the distance from the model surface of section to the actual surface of the measurement target.

In addition, when a surface belonging to multiple different body sections exists in the neighborhood, as in the cases of the armpit and crotch in the upright standing posture, the distance $r$ to the model surface of section does not differ much between the surface under consideration and the surface of another body section in the actual measurement target.

Consider, as an example, the relatively thin part of the waist, and assume that the surface of another body section, that is, the forearm, exists in the neighborhood [Fig. 4(a) $h_3$]. Then, the distance to the surface of the forearm does not differ much from the distance to the surface of the relatively thick part of the waist [Fig. 4(a) $h_1$]. This results in a situation in which the distributions of the distance $r$ from the acquired point cloud in the respective body section to the surface of the waist model overlap. In such cases it is difficult to exclusively extract all points acquired from the waist from the whole point cloud, regardless of what threshold $T_d$ is set for $r$. 

![Fig. 4. Clustering of points belong to each section of body.](image-url)
Since the surface has the properties of continuity and smoothness, the distance from the model surface of section to the surface of the corresponding body section does not change much locally. Considering locally the distance from the model surface of section it can be seen that the situation differs from the distance from the surface of the corresponding body section and the surface of other body sections, except for the joints.

Examing locally the distribution of the point cloud, the distributions of point clouds acquired from different body section surfaces do not overlap, and it is possible to segment them by means of a threshold [Fig. 4(b)]. The local distance distribution of the point cloud is investigated by dividing the side face of the cylinder for the model surface of section into meshes according to the values of (θ, h) [Fig. 4(c)], and the distribution of r of the point cloud is determined for each mesh.

In this method, discriminant analysis is applied in each body section to the distribution of the nearby points in the point cloud relative to the model surface of section and the threshold that divides the point cloud acquired from the surface of the body section under consideration and the point cloud acquired from the surface of another body section is determined.

Suppose that simple clustering is applied beforehand using the threshold T_d, and that the point cloud is extracted for each body section, with points belonging to at most two body sections locally. When the distribution of the point cloud with respect to r is composed of two single-peaked distributions, an appropriate threshold can be determined by constructing a histogram of the r component and applying discriminant analysis [8]. On the other hand, the distribution should not be divided if the point cloud forms a unique single-peaked distribution.

In this method, when the number of points having values of r close to the threshold obtained by discriminant analysis is larger than some threshold T_n, it is judged that the point cloud has a single-peaked distribution. When the point cloud in a mesh has two single-peaked distributions, it is judged that the distribution with the smaller r component is the correct distribution, and that the distribution with the larger component is representing the surface of another body section, provided that the two distributions are not due to data noise. Then, the points with an r component smaller than the obtained threshold are clustered into the body section under consideration.

### 3.2. Restriction of points clustered into multiple body sections

After applying the processing described in Section 3.1, there still remain points in the point cloud which are clustered into multiple body sections. However, if there remains a point which is clustered to multiple body sections in a part other than a joint, which should not be a connection, that point may generate a spurious surface that connects multiple body sections. In other words, except for joints, any point in the point cloud should be clustered uniquely into a single body section. Consequently, for points clustered to multiple body sections other than joints, the clustering destinations are limited to one.

In order to restrict the clustering destinations for a point which is clustered into multiple body sections, the results of clustering into the body section in this method are investigated for points within a certain distance (neighbor points) of the considered point.

There can be the following three cases for a point which is clustered into multiple body sections:

1. The point is at a joint and is clustered into the two body sections on the two sides of the joint.
2. The point is not at a joint but is clustered into two body sections.
3. The point is clustered into three or more body sections.

#### 3.2.1. Point at joint clustered into body sections on both sides

Consider the points near the junction of two connected body sections A and B. When the surface reconstruction of body sections is completed, some of such points form junctions between body sections. Thus, it is desirable that the point clouds of parts other than junctions should be clustered into one of the body sections, so that point clouds clustered into both body sections do not constitute a large fraction of the total.

Whether or not the point belongs to a junction is decided as follows, based on the situation of the neighbor points.

The clustering destination is judged to be body section A (B) in the following cases.

- All neighbor points are clustered into A (B) [Fig. 5(a)].
- Some neighbor points are clustered into A (B) and the rest are clustered into both A and B [Fig. 5(b)].

For the case of Fig. 5(c), namely, that

- there are three kinds of neighbor points—those clustered into A, those clustered into B, and those clustered into both A and B, the procedure is as follows.

If the neighbor points clustered into both are sufficiently few, they are clustered into both and retained as “overlap” in joining the body sections. When there are
many neighbor points which are clustered to both, the other points are processed first. Then the body section into which the neighbor points are clustered is determined again, and the clustering destination is restricted according to the situation of the neighbor points.

### 3.2.2. Points other than at joints clustered into two body sections

Points not at joints, which are clustered into two body sections, can produce a spurious surface in the surface reconstruction. Such points should be clustered into one of the body sections.

For each point clustered into two body sections A and B, the clustering destination is decided on the basis of the neighbor points. For a point clustered into two body sections, the distances $d_A$ and $d_B$ to the surfaces of body sections A and B, respectively, are determined. Then, we consider each of the neighbor points which are clustered into only one of body sections A and B, and the distance to the surface of the clustered body section is determined. Let the means be $d'_A$ and $d'_B$, respectively. Then, each point is clustered into the body section with the smaller value of $|d_A - d'_A|$ and $|d_B - d'_B|$.

### 3.2.3. Points clustered into three or more body sections

Points clustered into three or more body sections can be generated in various cases, such as when a joint is close to another body section, or when multiple joints are close together. In order to handle these various cases in a unified way, the number of body sections that are clustering destinations of the point cloud is reduced to two or less in this method by the following procedure.

Let a point clustered into three or more body sections be denoted by $p$. For the point $p_1$ closest to $p$, we investigate the number of body sections into which it is clustered. If the number of body sections into which $p_1$ is clustered is less than that of $p$, point $p$ is clustered into the same body sections as point $p_1$. The reason is that the probability is high that neighbor points are similarly clustered into body sections. The above procedure is iteratively applied until there are no more points clustered into three or more body sections. When the number of destination body sections for clustering is at most two, the clustering destination is restricted by the procedure described before.

### 3.3. Surface reconstruction

For each body section, the surface is reconstructed from the point cloud which is clustered into that body section. Except for the head, the fingers, and the toes, which have detailed structures, the sections of the human body can be considered to have shapes similar to cylinders or elliptical columns. It is assumed that the surface of the body section is composed of a cylindrical surface surrounding the main axis and faces closing both ends.

The point cloud data clustered into each body section are projected onto the cylindrical surface and the other faces, and a 2D Delaunay net is constructed on the projected surfaces. By applying the connection relation composed by the Delaunay net to the point cloud in the original 3D space, the surface is reconstructed. In order to avoid confusion with the 3D coordinate system, the 2D coordinate system is here represented by $u$ and $v$, not by $x$ and $y$.

### 3.3.1. Determination of curved surface for projection

The curved surfaces for projection are the surfaces of a cylinder, a hemisphere, an elliptic column, and an ellipsoid, which form the body section model [Fig. 6(a)]. In cases such as the neighborhood of the elbow joint in a posture with an extended arm, in which the end of the body section is not closed (a body section for which the length is not adjusted in Section 2.4), the point cloud is projected onto the face which is an extension of the cylinder or elliptic column surface composing that body section model, not onto the surfaces of the hemisphere or the ellipsoid [Fig. 6(b)].

### 3.3.2. Projection onto cylindrical surface

The point to be projected onto the cylindrical surface is represented by the 3D cylindrical coordinates $(r, \theta, h)$ defined in Section 3.1 [Fig. 7(a)]. The direction of the zero angle is set arbitrarily. The point at $(r, \theta, h)$ is projected onto $(R, \theta, h)$ ($R$ is the radius of the cylindrical surface for projection) [Fig. 7(b)]. Letting $u = R\theta$ and $v = h$, the point

![Fig. 5. Clustering of points belong to two sections of body around the joint. (a) Neighbor points clustered only into A; (b) Neighbor points clustered into A or into both; (c) Neighbor points clustered into A, into B, or into both.](image)
3.3.3. **Projection onto hemisphere**

The point to be projected onto a hemispherical surface is represented in the 3D polar coordinates \((r, \theta, \phi)\), with the center of the hemisphere as the origin [Fig. 8(a)]. The point at \((r, \theta, \phi)\) is projected onto \((R, \theta, \phi)\) \((R\) is the radius of the hemispherical surface for projection) [Fig. 8(b)]. Using the \(\theta\) and \(\phi\) components of the point on the projected hemispherical surface [Fig. 8(c)], the 2D coordinates \((u, v)\) are defined as \(u = R\phi \cos \theta\) and \(v = R\phi \sin \theta\) [Fig. 8(d)].

3.3.4. **Surface reconstruction of body section using Delaunay net**

For the projected point cloud, a 2D Delaunay net is constructed. Then, by applying the connection relations of the constructed Delaunay net to the point cloud in the original 3D space, the surface is reconstructed.

It is conceivable that the point cloud belonging to a body section may be divided into two or more groups according to the shape of the surface, and a Delaunay net is constructed separately for each of these. However, then the surface of the part connecting them is not formed. Consequently, in the course of projection, the range of projection onto the cylindrical surface is expanded so that the area of projection onto the hemispherical surface and the area of projection onto the cylindrical surface overlap. Then the Delaunay nets are constructed. Later, the spurious overlapping surface is deleted in order to construct the surface for the junction.

A similar situation arises when Delaunay nets are constructed for the point cloud projected onto a cylindrical surface. On the 2D surface formed by projection onto the cylindrical surface, the two ends (\(\theta = 0\) and \(\theta = 2\pi\)) represent the same position in 3D space. Consequently, points near \(\theta = 0\) are also projected into the neighborhood of \(\theta = 2\pi\), and points near \(\theta = 2\pi\) are also projected into the neighborhood of \(\theta = 0\). Then Delaunay nets are constructed. Later, the spurious overlapping surface is eliminated in order to construct the surface retaining the connection relations.
After constructing the surface for each body section, the surfaces of the body sections are connected. By the process described in Section 3.2.1, the surface is composed of points clustered only into the body section under consideration, and points clustered into multiple body sections. Consequently, the body sections can be connected directly by integrating the surfaces of the body sections.

In the course of surface reconstruction of a body section, there may exist a surface composed only of points clustered into multiple body sections. When the surfaces of the body sections are integrated, such a surface is located in a position which should be inside the body. Consequently, surfaces composed only of points clustered into multiple body sections are eliminated.

4. Experiment and Evaluation

4.1. Synthetic data

We simulated a shape measurement system to make some synthetic point cloud data.

In this study, the laser range finder is considered as the measurement system. The laser range finder is a system in which the laser light from a slit is projected onto an object and, by recording the reflected light with a camera, the distance between the object and the camera is determined by the principles of triangulation. The 3D coordinates of a point on the object surface can be determined from the positions of the camera and the object. Because of this mechanism, the acquired point is restricted to the range which can be illuminated by the laser light and observed by the camera. If either of the above conditions is not satisfied, that area is missing from the data.

The simulation data were made so as to express this property of the measurement system. The optical axis of the camera and the illumination direction of the laser light were specified first, and a system was considered in which the points on the surface of the measurement target (the human body model) that can be reached in the two directions were defined as the point cloud. Patch models for human postures were prepared, using the Poser3 software (Meta Creations Co.), which constructs 3D models of the human shape for the upright standing posture and other postures (10 in all). These models were defined as the measurement targets, and simulation data including self-occlusion were constructed.

Cameras were placed at the front and the rear of the 3D human body model. The angle to the laser illumination direction was assumed to be \((k/12) \pi\) \((k = 1, 2, 3)\), and the resolution of the camera was assumed to be approximately 10 mm near the body surface. The simulation data were constructed by the above procedure. Figure 9 shows the representation of the point cloud data, where simulation was applied to some postures by setting \(k = 1\). Figure 9(b) is an expanded figure which indicates that the point cloud is missing at the arms and legs due to self-occlusion.

4.2. Experiment with synthetic data

An experiment was performed in which the proposed method was applied to the simulation data in Fig. 9(a), and the surface was reconstructed.

First an attempt was made to use the method described in Section 2 to estimate the posture. Volume data were constructed from the point cloud data. Figure 10 shows the result of matching the human body model, and the result when the matching result is corrected by using the point cloud data. In the figure, in order to see how the human body model is modified in the two steps of the posture estimation process, the human body model before processing is shown by outlines, together with the human body model after processing. The upper limit of the voxel size was set as 40 mm, and the weight of the contour voxels was set as \(n = 2\).

It can be seen from the result that the upright standing posture can be estimated from the simulation data. It is also verified that by correcting the results of matching using the
Next, an experiment on surface reconstruction was performed. For comparison, the surface was also reconstructed by simple clustering using the threshold $T_d$, as described at the start of Section 3. Then, the proposed method was applied to the same point cloud data and the surface was reconstructed. Figure 11 shows the results. The threshold $T_d$ was set as 30% of each body section width. The number of mesh divisions for $(\theta, h)$ was set as 10 for both. The threshold $T_n$ was set as the maximum frequency of the point cloud in the mesh, multiplied by 0.05.

The following observations are made from the results. In simple clustering using the threshold, spurious surfaces are generated in surface reconstruction, filling the armpits and the crotch, but the proposed method markedly reduces the generation of spurious surfaces and reconstructs the whole body surface.

We also wanted to compare the 3D human body model as the target of measurement and with the surface reconstructed from the point cloud data. The surface reconstructed from the point cloud data and 3D human body model as the target of measurement were both represented using wire frames. Figure 12 compares these, together with the representations of the armpits and crotch.

We also attempted a more precise comparison of the 3D human body model as the target of the measurement with the reconstructed surfaces. Surfaces not present in the 3D human body model as the target of measurement were extracted by the following procedure.

For each patch of the surface reconstructed from the point cloud, we determined the patch of the original patch model from which its vertex was derived. The normals to the original patches were calculated and their average was determined. The average normal and the normals of the reconstructed patch were compared. If their difference was sufficiently small, it was judged that the reconstructed patch was on the surface of the original human shape. The above processing was applied to all reconstructed patches, and surfaces not existing in the 3D human body model as the target of measurement were extracted. Figure 13 shows the surfaces extracted by the above procedure in the wire-frame representation.

Comparing the 3D human body model as the target of the measurement and the reconstructed surfaces, it can be seen that the missing parts of the point cloud data form a surface which differs from the 3D human body model as the target of measurement. The reason seems to be that
processing such as estimation of missing parts is not included in the proposed method.

4.3. Experiment with measured data

An experiment was performed in which the proposed method was applied to point cloud data obtained by measurement of a real human body, and the surface was reconstructed. The human body measurement system used in this experiment had an error of 1.0 mm and a resolution of 2.0 mm.

Figure 14 shows the result obtained when the proposed method was applied to point cloud data obtained by measuring a human body in the upright standing posture. Points that were apparently noises were eliminated manually from the point cloud data. The results indicate that the proposed method is also effective in handling point cloud data obtained by real human body measurements.

4.4. Experiment on data from arbitrary posture

An experiment was performed in which the proposed method was applied to synthetic data and measured data for 10 different arbitrary postures constructed as described in Section 4.1, and the surface was reconstructed.

Figure 15(b) shows the result of posture estimation for one of the sets of synthetic data for an arbitrary posture.
constructed in Section 4.1 [Fig. 9(b)], and the result of surface reconstruction. It is seen that the postures are correctly estimated for all synthetic data for 11 human figures. It is also verified that the surface is reconstructed with little generation of spurious surfaces.

Figure 16 shows the point cloud data obtained by the measurement of a human body in a posture other than upright standing, and the result obtained by applying the proposed method. Noise elimination was not applied to the point cloud data. Thus, some spurious surfaces are present in the results of reconstruction due to the fact that the proposed method does not include noise processing. It will be necessary in the future to establish a method for noise elimination.

5. Conclusions

This paper has proposed a method for reconstruction of the human body surface, in which the posture is estimated from the point cloud obtained by measuring the human figure. The point cloud is clustered into the body sections, and the surface is reconstructed for each body section. Then the body surface is reconstructed while reducing the generation of spurious surfaces in concave regions, such as the armpits and crotch.

Experiments were performed using the simulated measurement data on the human body in the upright standing posture, and with real measured data. It was shown that the whole body surface can be reconstructed with little spurious surface generation by using posture estimation based on matching of the human body model to the point cloud data obtained by measurement, together with surface reconstruction for each body section from the point cloud clustered into that body section. It was also shown using synthetic data and measured data that the proposed method can be applied effectively to measured data for any posture, not just to data from the upright standing posture.

Problems left for the future are as follows.
• Adjustment of the body model according to the physical size of the measured individual
• Processing of surface areas missing due to self-occlusion
• Handling of data overlap (shift) and noise arising from the measurement system

Areas in which point cloud data are missing due to self-occlusion are handled as surfaces in this method by generating a small number of planes. It is conceivable that the missing area could be complemented by integrating multiple measurement results or by combining knowledge and statistical information concerning the human shape. In that case, a human body model estimated from partially measured data by the method of Nishida and colleagues [9] may be utilized as a priori information.

Furthermore, when the body shape is measured with laser range finders and other devices, it is difficult to measure the whole body with a single camera. Our approach is based on using multiple cameras at the same time, with the whole body shape acquired by integrating the measured data. This may lead to data overlap with deviations in the areas measured by multiple cameras. The correction of such cases is not included in the proposed method. It is left as a future problem to resolve these points and to establish a more useful reconstruction method for the human body surface.

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