# The NURBS Human Body Modeling Using Local Knot Removal

**Joon Woo Jo and Sung Soo Han***

*School of Textiles, Yeungnam University, Gyeongsan 712-749, Korea*

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**Abstract:** These days consumers' various demands are accelerating research on apparel manufacturing system including automatic measurement, pattern generation, and clothing simulation. Accordingly, methods of reconstructing human body from point-clouds measured using a three dimensional scanning device are required for apparel CAD system to support these functions. In particular, we present in this study a human body reconstruction method focused on two issues, which are the decision of the number of control point for each sectional curve with error bound and the local knot removal for reducing the unusual concentration of control points. The approximation of sectional curves with error bounds as an approximation criterion leads all sectional curves to their own particular shapes apart from the number of control points. In addition, the application of the local knot removal to construction of human body sectional curves reduces the unusual concentration of control points effectively. The results may be used to produce an apparel CAD system as an automatic pattern generation system and a clothing simulation system through the low level control of NUBS or NURBS.

**Keywords:** Human body modeling, NURBS, Fuzzy c-means algorithm, Surface approximation

## Introduction

Nowadays, for the garment manufacturing industry, there are extensive research of surface reconstruction of human body point data obtained using a three dimensional scanning device [1,2]. Variations and exceptions in the shapes of the human body, however, make automatic human body modeling extremely difficult. There are two primary stems for this problem. One is segment modeling which divides the human body into a number of segments [3]. The other is polygonal mesh reconstruction [4]. In this study, segment modeling is selected because the appearance of major parts of the human body is cylindrical surface. There are many methods for surface fitting as well. The most representative methods are implicit reconstruction techniques [5] and *surfaces from contours* [6]. We use *surfaces from contours* because isocurves of surface in parallel with sectional curves have many advantages for pattern generation. Accordingly, first, torso is selected as a segment and torso surface is reconstructed from sectional curves by skinning [7]. However, the skinning method using contours or sectional curves accompanies with explosive increment of non-necessary data and has a problem in the arbitrary determination of the control points of each sectional curve for approximation. In addition, the irregularity of sectional curve data causes the irregular control point distribution of sectional curves. Therefore, in this study, a methodology has been proposed to tackle the following issues in human body modeling.

1) The error bound dependent determination of control points for well posed approximated curves
2) The restriction of explosive increase of control points without recognizable distortion of the human body
3) The reduction of control point concentration of sectional curves.

*Corresponding author: sshan@yu.ac.kr

## NURBS Approximation

### The Least Square NURBS Approximation

In a parametric curve such as NUBS or NURBS, the fundamental condition that determines the shape of the curve is the number of control points and their positions. Meanwhile, we used surface reconstruction technique named skinning. Skinned surface [8] which is produced by skinning must pass exactly through the given sectional curves. Thus, it is important to determine the control points of sectional curves for defining the shape of the skinned surface. Skinned surface has a critical condition: all sectional curves must have the same number of control points. To satisfy this condition, the number of control points for all sectional curves can be set in advance. In spite of the simplicity of this method, it is somewhat difficult to find in advance how many control points are needed. The number of control points determined beforehand may not be sufficient for complex curves. On the contrary, it can be too large for representing simple curves. At the same time, it is necessary to repeat personal approximation process to find the proper number of control points. A method for avoiding these problems is to apply a least squares approximation with error bounds.

Assume that degree $p \geq 1$, control point index $n \geq 0$, and $\mathbf{Q}_n, \ldots, \mathbf{Q}_m (m > 1)$ are given. Then, a $p$-th degree non-rational curve is as follows.

$$\mathbf{C}(u) = \sum_{i=0}^{n} N_{i,p}(u)\mathbf{P}_i \quad u \in [0, 1] \tag{1}$$

$\mathbf{C}(u)$ satisfies $\mathbf{Q}_0 = \mathbf{C}(0)$, $\mathbf{Q}_m = \mathbf{C}(1)$, and the remaining $\mathbf{Q}_k$ can be approximated by the least squares method, i.e.,

$$f = \sum_{k=1}^{m-1} |\mathbf{Q}_k - \mathbf{C}(t_k)|^2 \tag{2}$$

is the minimum with respect to the $n + 1$ variables. The $t_k$ are parameter values predetermined by the cord length.

$$f = \sum_{k=1}^{m-1} |\mathbf{Q}_k - \mathbf{C}(t_k)|^2 = \sum_{k=1}^{m-1} \left|\mathbf{Q}_k - \sum_{i=0}^{n} N_{i,p}\mathbf{P}_i\right|^2 = \sum_{k=1}^{m-1} \left|\mathbf{Q}_k - \left\{\sum_{i=1}^{n-1} N_{i,p}\mathbf{P}_i + N_{0,p}\mathbf{P}_0 + N_{n,p}\mathbf{P}_n\right\}\right|^2 \quad (3)$$

where, $\mathbf{P}_0$ and $\mathbf{P}_n$ are equal to $\mathbf{Q}_0$ and $\mathbf{Q}_m$ respectively because the knot vector is non-uniform knot vector.

$$\begin{aligned} f &= \sum_{k=1}^{m-1} \left|\mathbf{Q}_k - \left\{\sum_{i=1}^{n-1} N_{i,p}\mathbf{P}_i + N_{0,p}\mathbf{Q}_0 + N_{n,p}\mathbf{Q}_m\right\}\right|^2 \\ &= \sum_{k=1}^{m-1} \left|\mathbf{R}_k - \sum_{i=1}^{n-1} N_{i,p}\mathbf{P}_i\right|^2 \\ &= \sum_{k=1}^{m-1} \left(\mathbf{R}_k - \sum_{i=1}^{n-1} N_{i,p}\mathbf{P}_i\right) \cdot \left(\mathbf{R}_k - \sum_{i=1}^{n-1} N_{i,p}\mathbf{P}_i\right) \\ &= \sum_{k=1}^{m-1} \left[\mathbf{R}_k \cdot \mathbf{R}_k - 2\sum_{i=1}^{n-1} N_{i,p}(t_k)(\mathbf{R}_k \cdot \mathbf{P}_i)\right] \\ &\quad + \sum_{k=1}^{m-1} \left[\left(\sum_{i=1}^{n-1} N_{i,p}(t_k)\mathbf{P}_i\right) \cdot \sum_{i=1}^{n-1} N_{i,p}(t_k)\mathbf{P}_i\right] \end{aligned} \quad (4)$$

According to the standard least square method for minimizing $f$, the derivatives of $f$ with respect to the $n-1$ points of $\mathbf{P}_l$ is

$$\frac{\partial f}{\partial \mathbf{P}_l} = \sum_{k=1}^{m-1}\left(-2N_{l,p}(t_k)\mathbf{R}_k + 2N_{l,p}(t_k)\sum_{i=1}^{n-1} N_{i,p}(t_k)\mathbf{P}_i\right) \quad (5)$$

And, is equal to zero. Therefore equation (5) becomes

$$\sum_{k=1}^{m-1} N_{l,p}(t_k)\mathbf{R}_k + \sum_{k=1}^{m-1}\sum_{i=1}^{n-1} N_{l,p}(t_k)N_{i,p}(t_k)\mathbf{P}_i = 0 \quad (6)$$

It follows that

$$\sum_{i=1}^{n-1}\left(\sum_{k=1}^{m-1} N_{l,p}(t_k)N_{i,p}(t_k)\right)\mathbf{P}_i = \sum_{k=1}^{m-1} N_{l,p}(t_k)\mathbf{R}_k \quad (7)$$

The matrix notation of equation (7)

$$(\mathbf{N}^T\mathbf{N})\mathbf{P} = \mathbf{R} \quad (8)$$

An approximation curve can be represented using control points calculated from equation (8). A three dimensional scanning device manufactured by CyberWare was used to produce a number of sectional point-clouds at every 0.002 m interval representing the surface of a human body. Figure 1 represents raw data, which are 21 sectional point-clouds extracted from all point-clouds within the range from 0.788 m to 1.388 m in height. Figure 2 is an approximation curve obtained at 1.298 m in height by setting the number of control point at 35 arbitrarily.

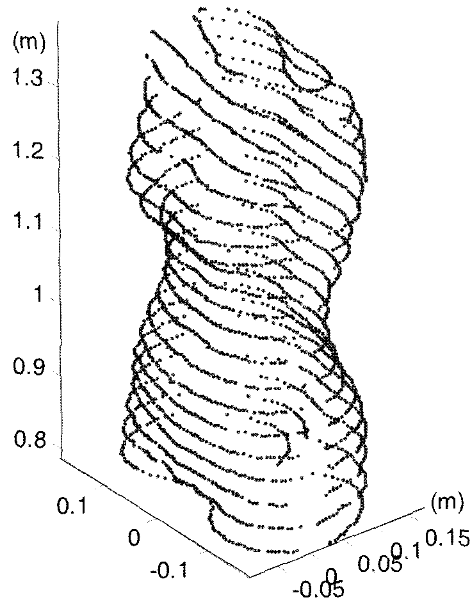


**Figure 1.** Cross sectional point data of a torso.

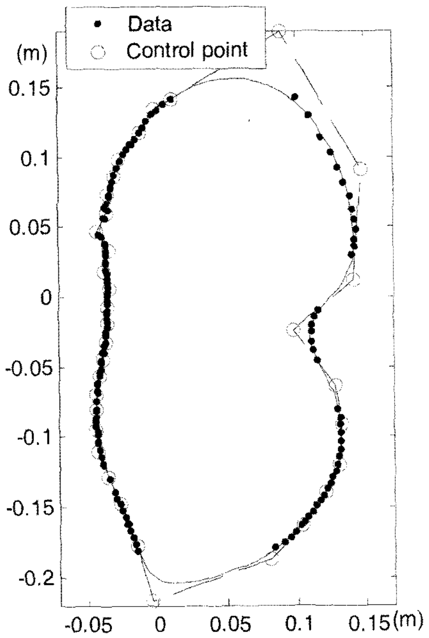


**Figure 2.** An approximation curve for the selected sectional curve.

## Determination of the Number of Control Point with Error Bound

When sectional data are approximated by the method introduced in the previous section, a reasonable criterion for approximation is necessary. For this purpose, in our approach,

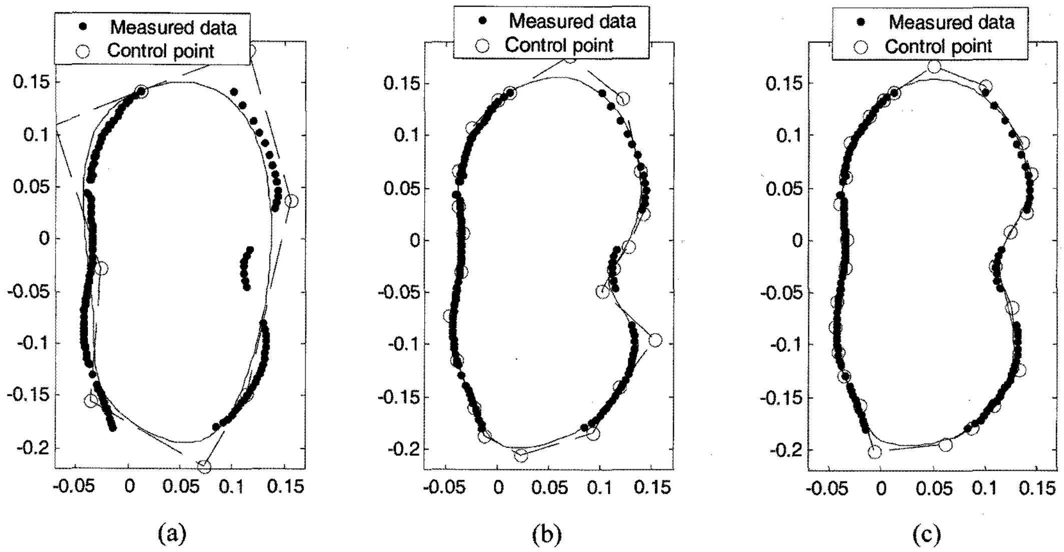


**Figure 3.** Effects of error bound on the shape of approximation curves: (a) error bound = 0.05, (b) error bound = 0.01, and (c) error bound = 0.007.

the deviations of a sectional curve from each measured point was calculated by point projection [9] and then approximation and iteration were continued until the maximum deviation became less than the specified error bound. The first step toward approximating a sectional curve is to interpolate the given sectional point data. When the interpolation process is completed, the knots of the interpolation curve can be removed as many as possible while maintaining the specified error bound by knot removal [10]. Next, we iterate approximation by increasing the number of control points until the maximum deviation is within the user specified error bound. Figure 3(a), (b) and (c) are approximation curves with 0.05 m, 0.01 m and 0.007 m error bounds respectively. The approximation curves in Figure 3(a), (b) and (c) have 9, 23 and 27 control points respectively. These results clearly show that the curve is approximated by its appearance within the specific error bound.

## Local Knot Removal

The unusual concentration of point data is shown on the left side in Figure 2. Besides, the control point concentration can be found on the side, in which the curvature is low and the density of point data is high. The fact that there is a region with low curvature and high density of control points make NURBS approximation inefficient. The chord length method [9] for determining $t_k$ in equation (2) causes this phenomenon. To reduce the concentration, we use local knot removal that removes knots within a specified region. If knot removal can be applied to a certain region, knot removal is much more efficient than the process removing knots in entire knot vector. That is, local knot removal can restrict additional deviation within the specified region. Figure 5 represents knot values for 21 sectional curves. At domain [0, 1], the left region with many knot values has the problem of control point concentration. In addition, this region must not have many control points because it is a low curvature region. Local

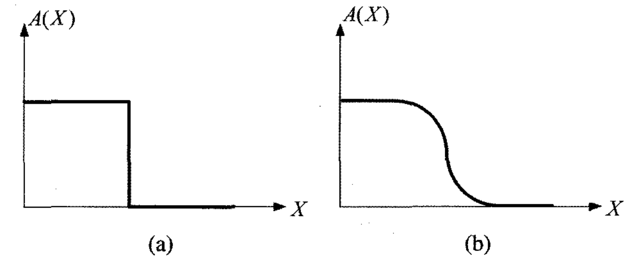


**Figure 4.** Membership functions: (a) crisp set, (b) fuzzy set.

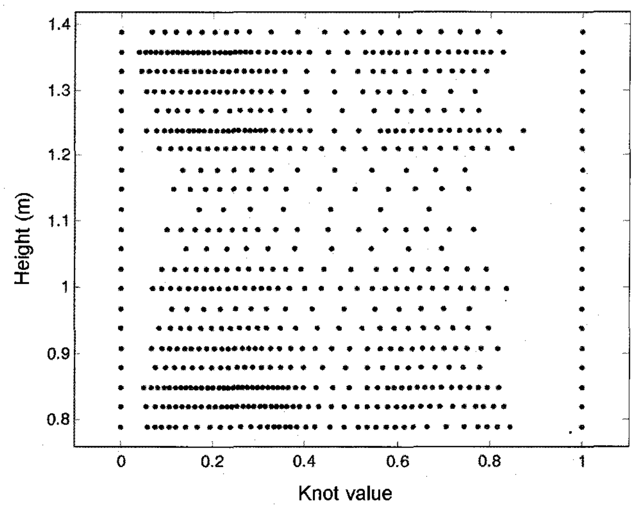


**Figure 5.** The distribution of knot values.

**Table 1.** The number of control points before and after local knot removal (The number of control points before local knot removal: $N_b$, the specified interval for local knot removal: $\Omega$, the number of control points after local knot removal: $N_a$)

| Height (m) | $N_b$ | $\Omega$ | $N_a$ | Percentage (%) |
|---|---|---|---|---|
| 1.388 | 25 | [0 , 3.8279705e-001] | 20 | 20.0 |
| 1.358 | 51 | [0 , 4.0626891e-001] | 34 | 39.2 |
| 1.328 | 37 | [0 , 4.0246232e-001] | 25 | 35.1 |
| 1.298 | 30 | [0 , 4.0292069e-001] | 20 | 33.3 |
| 1.268 | 25 | [0 , 4.0824982e-001] | 21 | 20.0 |
| 1.238 | 47 | [0 , 4.6223488e-001] | 31 | 36.1 |
| 1.210 | 31 | [0 , 4.3620830e-001] | 23 | 21.6 |
| 1.178 | 16 | [0 , 3.8223445e-001] | 14 | 18.7 |
| 1.148 | 18 | [0 , 4.2867241e-001] | 14 | 22.2 |
| 1.118 | 11 | [0 , 4.2867241e-001] | 11 | 0.0 |
| 1.088 | 21 | [0 , 3.8138002e-001] | 15 | 28.5 |
| 1.058 | 14 | [0 , 3.7706482e-001] | 12 | 21.4 |
| 0.028 | 26 | [0 , 4.4109668e-001] | 19 | 26.9 |
| 0.998 | 36 | [0 , 4.3498176e-001] | 27 | 33.3 |
| 0.968 | 19 | [0 , 4.1593721e-001] | 16 | 26.3 |
| 0.938 | 29 | [0 , 4.2583999e-001] | 19 | 37.9 |
| 0.908 | 36 | [0 , 4.2042784e-001] | 25 | 35.8 |
| 0.878 | 32 | [0 , 4.3851441e-001] | 20 | 37.5 |
| 0.848 | 53 | [0 , 4.2353599e-001] | 33 | 43.3 |
| 0.818 | 50 | [0 , 4.2834535e-001] | 36 | 32.0 |
| 0.788 | 40 | [0 , 4.0074481e-001] | 30 | 26.8 |

knot removal consists of two stages. In the first stage we cluster the knot values to two groups. One is dense and the other is sparse. The second stage is general knot removal process except that the removal region is limited. In this study, for clustering in the first step, we use the classical fuzzy c-means algorithm [11]. A fuzzy set is a pair $(X, A)$, where $A$: $X \rightarrow I$ and $I = [0, I]$ and $X$ is a non-empty set. $A$ is called the membership function [12]. The family of all fuzzy sets on the $X$ will be denoted by $L(X)$. Thus $L(X) = \{A \mid A: X \rightarrow I\}$. The notion of fuzzy set has been introduced by L.A. Zadeh. $A(X)$ is the membership degree of $x$ to $A$. It may also be interpreted as the plausibility degree of the affirmation '$x$ belongs to $A$'. If $A(x) = 0$, $x$ is 'definitely not in $A$' and if $A(x) = 1$, $x$ is 'definitely in $A$'. The intermediate cases are 'fuzzy'. Figure 4 is the graphical representation of the membership function. Thus, fuzzy c-means algorithm is to make two fuzzy sets representing two clusters respectively. The membership degrees of these fuzzy sets are determined according to the similarity between any measured data and the center of the clusters. First, we map [0, 1] to [0, 1][0, 1] by using parametric representation for a circle.

$$\begin{cases} x(t) = \sin(t) \\ y(t) = \cos(t) \end{cases} \quad (0 \le t \le 2\pi) \tag{9}$$

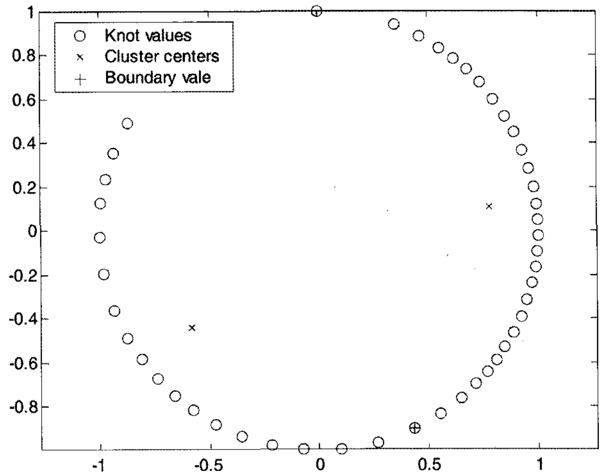

**Figure 6.** The result of clustering at 0.818 m in height.

Circular mapping is for uniting two dense regions that may be placed at the ends of [0, 1]. Next, the fuzzy c-means algorithm clusters the circular data to two regions. Figure 6 is the result of clustering the knots of a sectional curve at 0.818 m in height. We can select easily a sparse region based on the mean distance among the knots. The results of clustering for each sectional curves are shown in Table 1. Table 1 also shows the comparison of the number of control points between when local knot removal is adopted and when it is not. Figure 7 is the result of sectional curve approximation before local knot removal. Figure 8 is the result after local knot removal. 10 curves whose control points had been removed most plentifully were selected to verify the effect of local knot removal clearly. From the figures, we can see that additional data have been reduced in limited region.

**Surface Fitting**

For generating a skinned surface, the sectional curves constructed in the previous section must have the same number of control points and has to be defined over the same knot vector. Therefore, all knot vectors of the sectional curves need to be united. By uniting knot vectors using a knot insertion method called knot merge iteratively, only one knot vector can be obtained. This merged knot vector satisfies the important condition that entire interior knots must have single multiplicity [9]. A simple example is presented as follows

$$\left.\begin{array}{l} \{0, 0, 0, 0, 0.5, 1, 1, 1, 1\} \\ \{0, 0, 0, 0, 0.2, 0.3, 0.6, 0.8, 1, 1, 1, 1\} \\ \{0, 0, 0, 0, 0.2, 0.5, 0.7, 1, 1, 1, 1\} \end{array}\right\} \Rightarrow \text{Knot merge}$$

$$\Rightarrow \{0, 0, 0, 0, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 1, 1, 1, 1\}$$

{0, 0, 0, 0, 0.2, 0.3, 0.5, 0.6, 0.7, 0.8, 1, 1, 1, 1} has

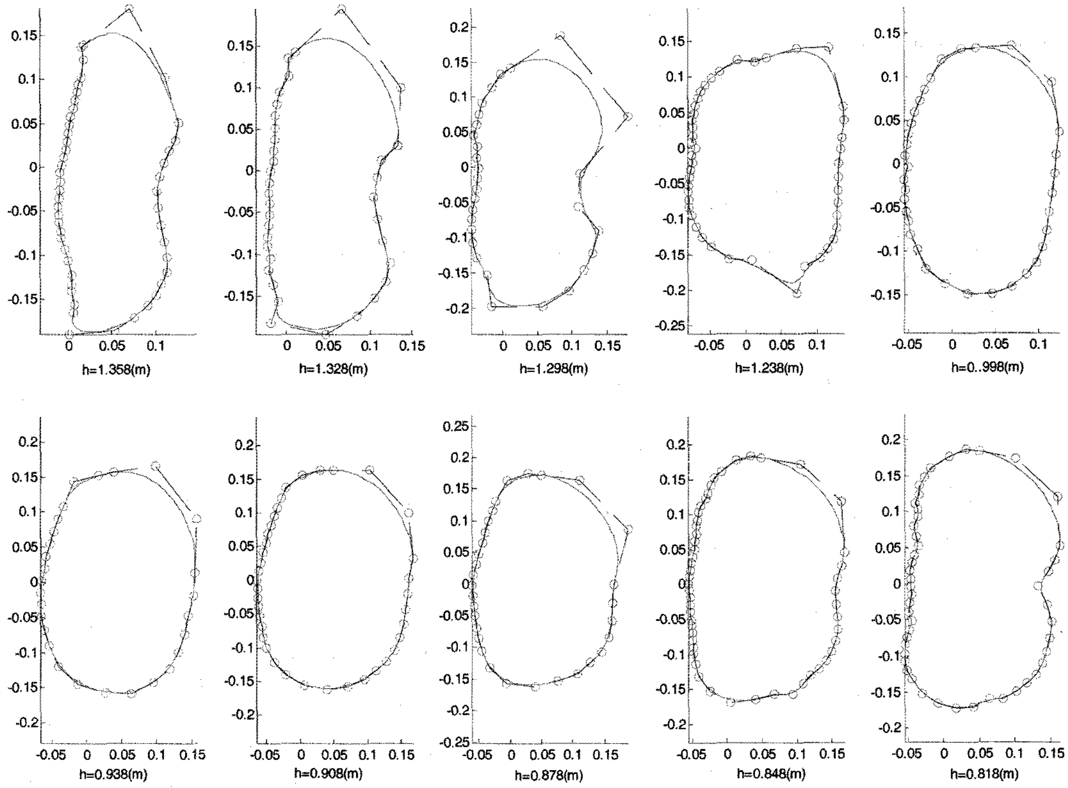


**Figure 7.** Some sectional curves before local knot removal.

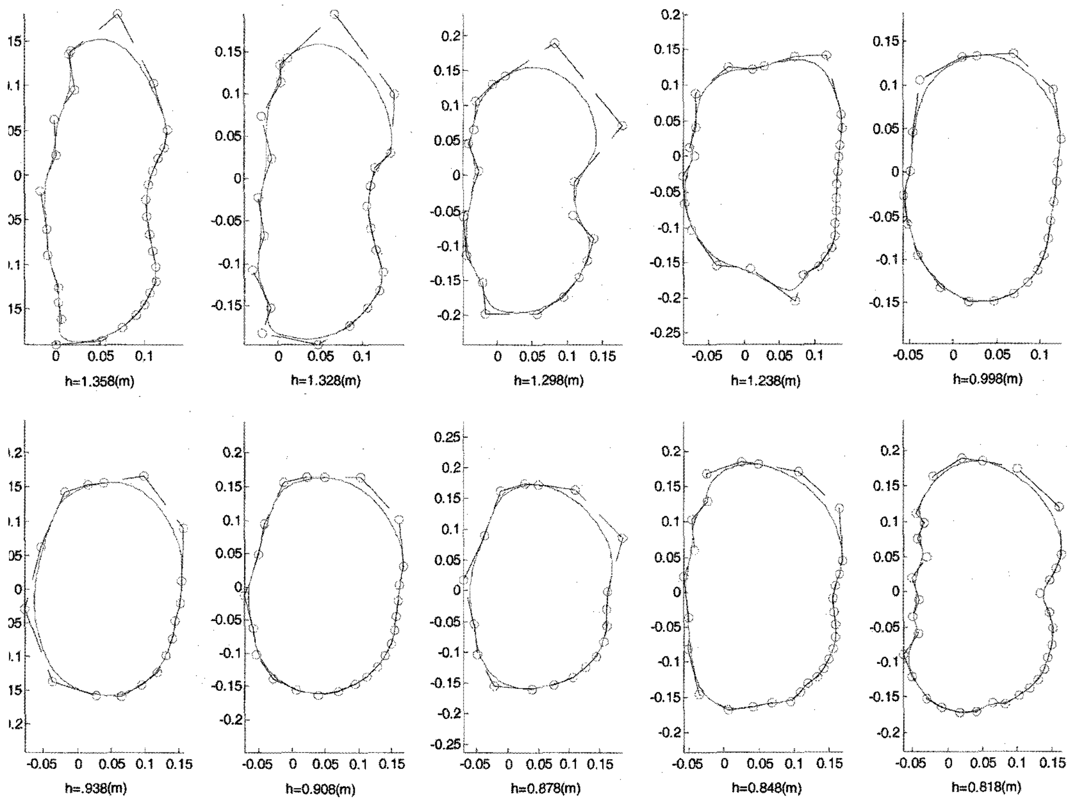


**Figure 8.** Some sectional curves after local knot removal.

**Table 2.** Results of tolerance allocation (number of knots after knot merge: $N_{am}$, number of knots after knot removal: $N_{ar}$)

| $e_c = 0.007$<br>Local knot removal was not carried out<br>$e_s = 0.007$ | | $e_c = 0.007$<br>$e_{lc} = 0.007$<br>$e_s = 0.007$ | | $e_c = 0.007$<br>$e_{lc} = 0.006$<br>$e_s = 0.007$ | |
|---|---|---|---|---|---|
| $N_{am}$ | $N_{ar}$ | $N_{am}$ | $N_{ar}$ | $N_{am}$ | $N_{ar}$ |
| 571 | 27 | 366 | 34 | 385 | 28 |

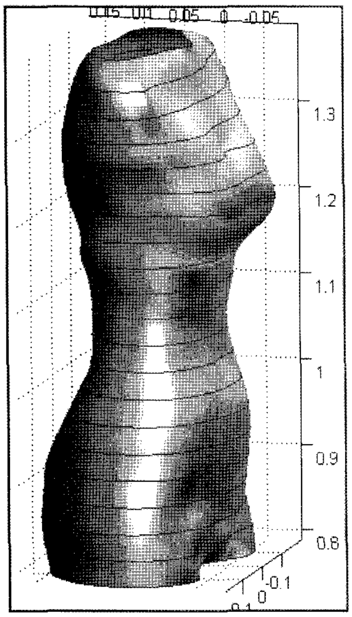


**Figure 9.** Torso surface with cross sectional curve.

multiplicity of 1 for all interior knots. In other words, the interior knots of the result knot vector are the union of the interior knots of all knot vectors of the sectional curves. However, knot merge results in an astonishing number of control points of sectional curves. The increase of the number of knot vector components increases the number of control points. Thus, after merging knots, a knot removal procedure has to be executed within the specified error bound for removing surplus control points. In this study, we compared two cases of surface fitting for verifying the effect of local knot removal on skinning. One is the result of surface fitting using local knot removal but the other did not use local knot removal. Table 2 summarizes the result, in which $e_c$ is tolerance for sectional curve approximation, $e_{lc}$ is tolerance for local knot removal, and $e_s$ is tolerance for knot removal after knot merge. As shown in Table 2, it turns out that the case without using local knot removal is much more efficient in that the more knots is removed. This is because deviation from measured point data increased additionally when local knot removal was carried out. Thus, we could improve removal performance to some degree using local knot removal tolerance lower than the final tolerance. Figure 9 illustrates the body surface and its the sectional curves at different locations. The body surface also satisfies all section curves.

## Conclusions

We have presented a method of constructing the human body for digitized CAD of apparel. There are two major issues in this method. One is the decision of the number of control point for each sectional curves with error bound and the other is the local knot removal for reducing the concentration of control points. The method presented for determining the number of control points according to specified error bounds facilitates each sectional curve to reflect its unique shape features more appropriately in such a way that the designer does not need to rely on the trial and error method. In addition, local knot removal was presented for removing control point concentration according to the irregularity of distribution of point data. While most of the previous researches on curve fitting did not adopt fuzzy logic algorithm, to determine the control point concentrated region, we have applied fuzzy clustering. Although it did not affected notably the number of control points of skinned surface, for saving sectional curve data or for contour trace using sectional curve data, it could reduce control points efficiently without unintended distortion in view of effective reduction of control points. In future study for reconstructing the human body, if an improved algorithm is developed for determining a control point concentration region considering the wiggle of curves and knot density together, we may approximate curves much more effectively and reconstruct the human body using NURBS sectional curves.

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