# 3D Posture Representation Using Meshless Parameterization with Cylindrical Virtual Boundary

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**Abstract.** 3D data is getting popular which offers more details and accurate information for posture recognition. However, it leads to computational hurdles and is not suitable for real time application. Therefore, we introduce a dimension reduction method using meshless parameterization with cylindrical virtual boundary for 3D posture representation. The meshless parameterization is based on convex combination approach which has good properties, such as fast computation and one-to-one mapping characteristic. This method depends on the number of boundary points. However, 3D posture reconstruction using silhouettes extraction from multiple cameras had resulted various number of boundary points. Therefore, a cylindrical virtual boundary points is introduced to overcome the inconsistency of 3D reconstruction boundary points. The proposed method generates five slices of 2D parametric appearance to represent a 3D posture for recognition purpose.

**Keywords:** 3D voxel, dimension reduction, meshless parameterization, posture recognition, cylindrical virtual boundary.

## 1 Introduction

The latest advances in computer vision have gained much attention especially for 3D posture recognition application. The 3D data offers more details and accurate posture information compare to 2D posture data. However, it leads to computational hurdles and is not suitable for real-time posture recognition. Therefore, 2D posture recognition application has attracted more researchers' bias towards it [10, 15, 16]. The main reason is the simplicity and reasonable processing time for posture recognition application. Still the 2D posture recognition only restricts to particular applications or methods to deliver the input pose. For example, sign-language recognition application [8, 14] which captures the 2D posture from a camera. However, the 2D input is not able to estimate some pose which caused by image projection and self-occlusion. The user might be facing away from the camera, hiding the pose, or some objects could block the camera's view of the user. Therefore, the input pose has limits on the space in which posture can be recognized. And it creates additional burden on the user of staying alert for this restriction.

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D. Mery and L. Rueda (Eds.): PSIVT 2007, LNCS 4872, pp. 449–461, 2007.

In order to make the posture recognition application more meaningful and resourceful, 3D posture recognition becomes a challenging and active research in computer vision field. Multiple cameras usages are introduced to solve the limitation of placing model position. There are various kinds of approaches for 3D posture data reconstruction, some well known methods such as space carving, Shape-From-Silhouettes (SFS), visual-hull reconstruction, voxel-based and etc [9].

In this paper, we focus on a dimension reduction method for 3D posture representation. The key idea of dimension reduction method is to overcome the computational hurdles of 3D posture recognition and preserved the 3D information. There are various kinds of approaches to apply for dimension reduction of 3D to 2D such as principal component analysis (PCA), multidimensional scaling (MDS), local linear embedding (LLE) and etc [14, 17].

PCA constructs a low-dimensional representation of the data that describes as much the variance in the data as possible. It is done by finding a linear basis of reduced dimensionality for the data. The main drawback of PCA is that the size of covariance matrix is proportional to the dimensionality of the data points. MDS represents a collection of nonlinear techniques that maps the high dimensional data representation to a low dimensional representation while retaining the pairwise distances between the data points as much as possible. The quality of the mapping is expressed in the stress function, a measure of the error between the pairwise distances in the low dimensional and high dimensional representation of data. LLE is a local nonlinear technique for dimension reduction which constructs a graph representation of the data points. It attempts to preserve local properties of the data manifold in the low dimensional representation of data points. However, these approaches are not able to preserve the posture information.

Since the 3D posture reconstruction using SFS results voxel as point clouds form. Then, the 3D posture representation over 2D domain using meshless parameterization is introduced. This method is known for parameterizing and triangulating single patch on unorganized point sets. The convex combination approach in meshless parameterization has good properties, such as fast computational and one-to-one mapping characteristic [1-4]. Therefore, we chose meshless parameterization instead of the others approach for dimension reduction. However, the existing method of meshless parameterization is hardly to analyze the posture due to 3D voxel reconstruction drawback: inconsistency of boundary points where the boundary shape is deformed when captured from multiple cameras. In this paper, cylindrical virtual boundary is introduced to overcome the boundary point's drawback. The cylindrical virtual boundary provides a consistent boundary shape. The results of meshless parameterization over 2D are studied and analyzed for matching purpose.

An overview of our proposed approach is illustrated in Fig. 1. In this paper, the 3D posture data is reconstructed using SFS method where the silhouettes images are extracted from four web cameras. We introduce meshless parameterization using cylindrical virtual boundary and divide the 3D posture data into five segments for dimension reduction. This process overcomes the complexity of 3D posture data computation and it makes the recognition process more accurate and robust.

The various related works of posture or gesture recognition is presented in Section 2. Section 3 describes the details of posture modeling using dimension reduction method on 3D posture data into five slices of 2D parametric appearance. The dimension reduction process is using meshless parameterization with cylindrical virtual boundary. Posture analysis is written in Section 4, for matching purpose. The experimental results of posture recognition are elaborated in Section 5. Conclusion and future work are presented in Section 6.

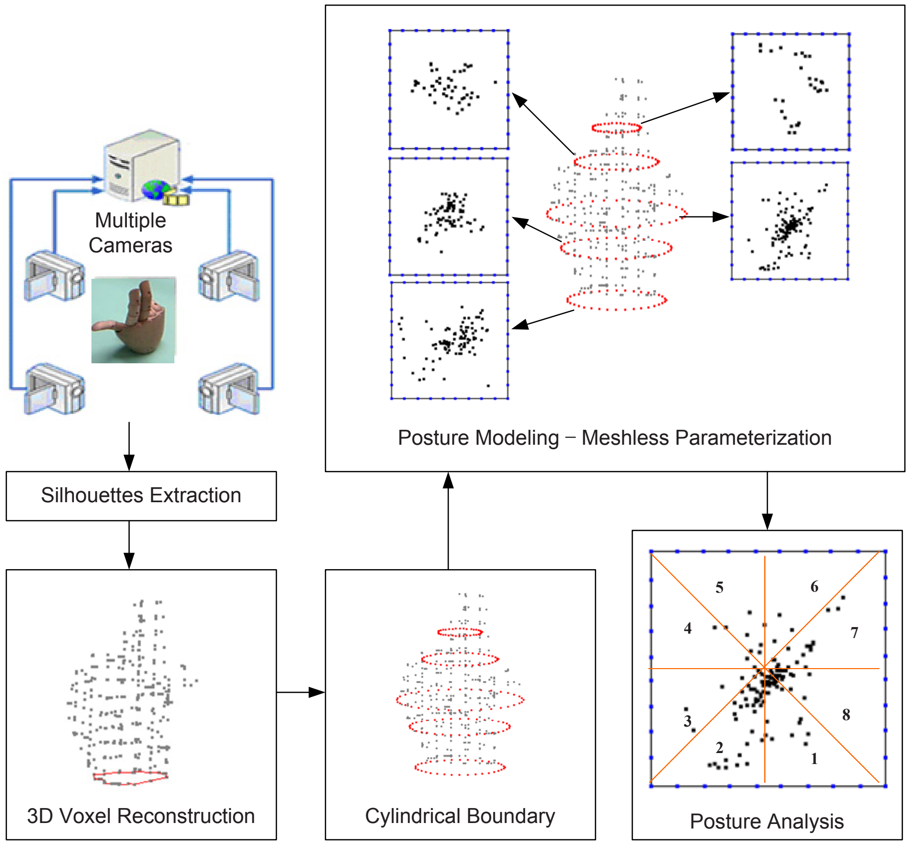



**Fig. 1.** Overview of the proposed system: from 3D voxel reconstruction, to dimension reduction using meshless parameterization, until posture analysis for recognition purpose

## 2 Related Work

There are various aspects involved in posture or gesture recognition, such as modeling, analysis, recognizing and etc. Therefore, recognizing posture is a complex task. In this section, we discuss the methods that have been proposed for posture or gesture recognition that involves in computer vision [5-16]. Generally posture recognition methods in vision-based can be divided into two categories: 3D model and 2D appearance modeling. 3D model provided more details and precise posture data compared to 2D, however, this approach is too complex and expensive for computation. Hence, 2D appearance has low computational complexity and many applications are adopted this approach. Somehow, 2D appearance has limited information of posture data due to the self-occlusion and projection error.

Kenny Morrison et al. [10] made an experimental comparison between trajectory-based and image-based representation for gesture recognition. The trajectory-based representation depends on tracking system which provides the temporal features of movement. The image-based recognition computed the values of pixel histories from image sequence and performed matching algorithm, such as statistical matching. Both approaches have its strengths and weakness.

Usually, the Hidden Markov Model (HMM) is used for recognizing gesture where the 3D model is fitted to silhouettes images or extracted data, or analyze the raw data. This make the HMM process complex and computational expensive. Chi-Wei Chu and Isaac Cohen [9] introduced a method for posture identification, called atoms. By modeling the atom transition and observation, the state transition and HMM computational complexity is reduced. H.K. Shin and et al. [6] proposed 3D Motion History Model (MHM) for gesture recognition. Their method is using stereo input sequences that contain motion history information in 3D space and overcome the 2D motion limitation like viewpoint and scalability.

Guangqi Ye and et al. [5] presented 3D gesture recognition scheme that combines the 3D appearance and motion features by reducing the 3D features with employing unsupervised learning. The proposed method is flexible and efficient way to capture the 3D visual cues in a local neighborhood around the object. Daniel Weinland at el [11] introduced motion descriptors that based on motion history volumes with advantage to fuse the action cues from different viewpoints and in short period, into a single three dimensional representation.

Xiaolong Teng et al. [14] proposed a real-time vision system to recognize hand gestures for sign language using linear embedding approach. They identified the hand gesture from images of normalized hand and used local linear embedding for feature extraction.

In our proposed approach, we are using 2D silhouettes images to reconstruct the 3D voxel and apply dimension reduction on 3D voxel using meshless parameterization with cylindrical virtual boundary. The result of five slices of 2D parametric appearance model is used for posture analysis and recognition purpose.

## 3 Posture Modeling

The posture modeling process is difficult and complex to represent in 3D voxel. The meshless parameterization is introduced to represent the 3D point's data into 2D representation which adopts good characteristics of convex combination such as fast computation and one-to-one mapping. However, this approach only works well for 3D voxel with consistent boundary shape. In the process of the 3D voxel reconstruction, the deformation of boundary shape occurs quite often. The meshless parameterization method depends on the boundary shape information. It will cause a poor result of the dimension reduction of 3D voxel into 2D representation.

Section 3.1 briefly describes the basic idea of meshless parameterization and followed by section 3.2, introduction of cylindrical virtual boundary in meshless parameterization to solve the drawback of existing approach.

### 3.1 Basic Idea: Meshless Parameterization

Meshless parameterization is a 2D parametric representation with some convex parameter where the one-to-one mappings of 3D voxel over 2D domain without using mesh information [1-4]. The method is divided into two basic steps. First, map the boundary points $P_B$ into the boundary of domain $D$ plane. Then, the corresponding parameter points $U = \{u_{n+1}, u_{n+2}, \ldots, u_N\}$ are laid around the domain $D$ counter-clockwise order. The chord length parameterization is used for the distribution of parameter points $U$.

The second step, the interior points are map into the domain $D$ plane. However, before mapping, a neighborhood $p_j$ for each interior point in $P_I$ where the points are some sense close by is chosen, and let $N_i$ as a set of neighborhood points of $p_i$. In this case, a constant radius $r$ is chosen. The points that fall within the ball with radius $r$ are considered the neighborhood points of each interior point. Then, the reciprocal distance weights method is to compute the weight $\lambda_{ij}$ for each interior point $pi$. The parametric points for interior point's $u_i$ can be obtained by solving the linear system of n equations of the number of interior points.

Fig. 2 illustrated the process of 3D voxel data in 2D parametric representation using existing method of meshless parameterization. However, the existing method has two drawbacks: first, the initial starting point is different for each posture generated from 3D voxel, and second, the boundary shape extracted from silhouettes generates variation of boundary shape. This both drawbacks cause the difficulties for posture analysis and recognition. In order to solve these problems, cylindrical virtual boundary is generated on 3D voxel before performing meshless parameterization. The details approach of cylindrical virtual boundary in meshless parameterization is presented in Section 3.2.

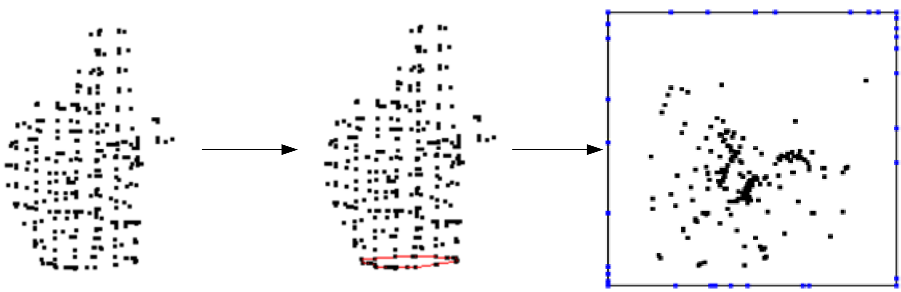


**Fig. 2.** The process of 2D parametric representation for 3D hand posture using the existing meshless parameterization

### 3.2 Cylindrical Virtual Boundary

The cylindrical virtual boundary is introduced to overcome the inconsistence shape of 3D posture boundary. It is derived by computing the 3D voxel bounding area and identifies the center of the voxel data as the center point of cylindrical. The cylindrical radius is derived based on the length distance between the minimum and maximum voxel points of x-axis. The x-axis is chosen as reference axis for cylindrical virtual boundary in our system. The cylindrical virtual boundary does not apply to whole 3D voxel data, there are only five cylindrical virtual boundaries place within the 3D voxel. This created five segments which consist of some interior points as interior points set and a cylindrical virtual boundary as boundary points set for each segment. Thus, for each segment of cylindrical virtual boundary, the radius size depends on the voxel data size for that particular segment. In our experiments, we are using an artifact hand model and real human posture. The size for the models is suitable to divide into five segments.

The meshless parameterization method is applied for each segment. The voxel data in each segment $P_I=\{p_1,p_2,\ldots,p_n\}$ as a set of interior points with n points, and $P_B=\{p_{n+1},p_{n+2},\ldots,p_N\}$ as set of boundary points with $N$-$n$ points which is corresponding to the number of cylindrical virtual boundary points. The constant radius $r$ in section 3.1 for computing the number of neighbors for each interior is set based on the radius size of the cylindrical virtual boundary. Therefore, the meshless parameterization with cylindrical virtual boundary generates five slices of 2D parametric appearance representation. Fig. 3 shows the basic idea of cylindrical virtual boundary for 3D voxel which is divided into five segments and each segment of cylindrical virtual boundary act as corresponding boundary points for each segment. The number of cylindrical virtual boundary points is equal to all five segments.

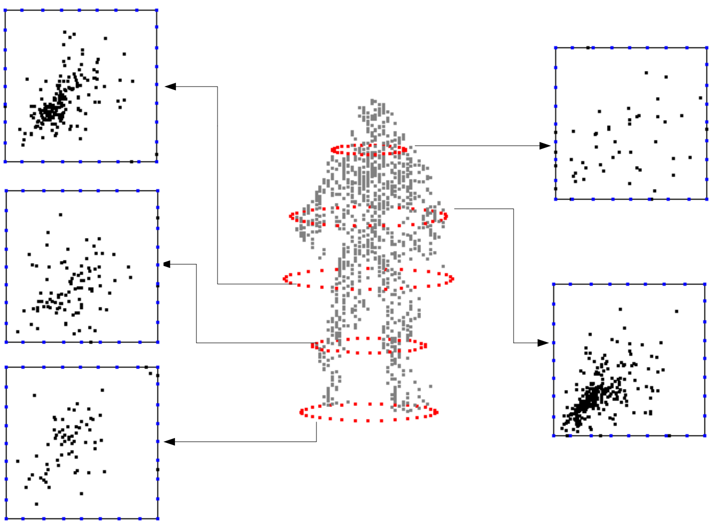


**Fig. 3.** The 3D voxel data of human pose is divided by five segments and each segment has a cylindrical virtual boundary. Each segment of cylindrical virtual boundary and 3D interior points are transform over 2D parametric domain using meshless parameterization.

### 3.3 Meshless Parameterization with Cylindrical Virtual Boundary Algorithm

This meshless parameterization works well on a surface patch with open disc of 3D posture data. Our proposed approach for meshless parameterization with cylindrical virtual boundary is described as below algorithm:

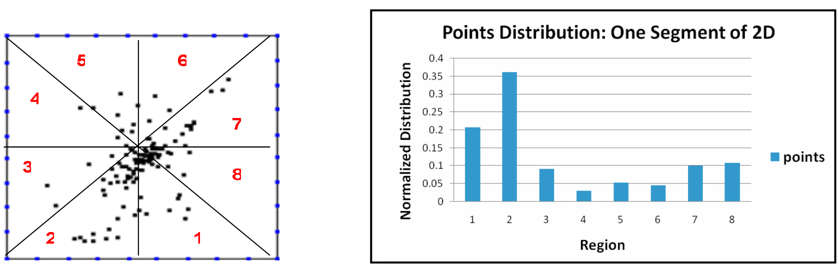
1. *Find the minimum and maximum voxel data of 3D voxel*
2. *Compute the center points of the 3D voxel*
3. *Divide the 3D voxel into 5 segments based on the min-max of z-axis*
4. *For each segments with n number of voxel data:*
    - i. *Find the minimum and maximum of voxel data*
    - ii. *Compute the radius for cylindrical virtual boundary*
    - iii. *Generate the cylindrical virtual boundary with a constant distribution*
    - iv. *Set the cylindrical virtual boundary as boundary points and voxel points as interior points*
    - v. *Map the cylindrical virtual boundary points into 2D domain of 1 unit size*
    - vi. *Set the constant radius r = radius of cylindrical virtual boundary to compute the number of neighbor points of each interior point and using reciprocal distance to compute the weights*
    - vii. *Solve the n linear equations*
    - viii. *Map the interior parameter values onto the 2D domain*

# 4 3D Posture Representation

The result of meshless parameterization with cylindrical virtual boundary generates five slices of 2D parametric appearance separately, named it as multi layers 2D appearance. This result is preceded for analysis and matching purpose. In posture recognition, template matching using 2D pixel points is the simple and easy approach by dividing the 2D domain into eight regions. However, the multi layers of 2D appearance have various orientations for each pose. Thus, the 2D appearance is divided into eight regions from the center point. The cylindrical virtual boundary is uniform for five segments, the regions division makes it possible for pixel points matching. All the matching process will be based on the same clockwise orientation from highest pixel points region.

## 4.1 Multi Layers of 2D Appearance

The result of multi layers of 2D appearance represents a 3D posture. It consists of five slices of 2D parametric appearance. Each slice is divided into 8 regions through the

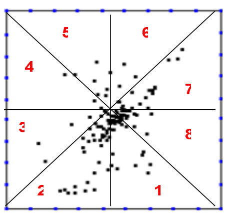



(a) (b)

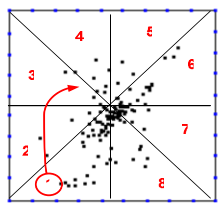
**Fig. 4** (a) One of segment slice in 2D parametric appearance which is divided into eight regions from the domain center point; (b) Graph of normalized distribution of each region pixel points in 2D slice segment center of 2D domain. We had chosen eight division regions for the best matching region purpose due to small Euclidean distance of voxel data distribution and cylindrical virtual boundary distribution. Another reason is to perform a fast processing, so it is possible to apply real-time posture application. The number of pixel points in each region is computed and represented into a graph as shown in Fig. 4 for one segment.

### 4.2 Synchronization of Starting Region

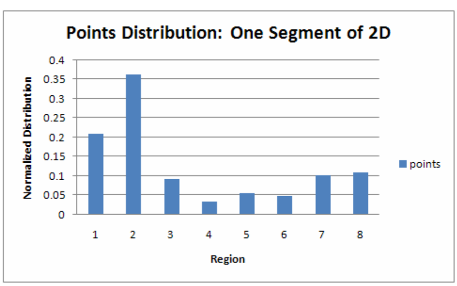
The eight division regions do not provide the posture orientation information for matching purpose. Therefore, the number of pixel point's distribution in each region is re-ordered to ease the matching. From the graph distribution, the highest number of pixel points of the region is referred as a starting region. And from the start region, the matching process is continuing to match within the region in clockwise order of the regions from the 2D parametric appearance. Fig. 5 shows the method of choosing the starting region, which based on the highest number of pixels region. The regions are ordered in clockwise order distribution is shown in the represented graph.



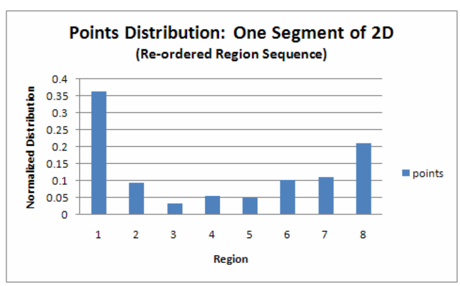

(a) Original distribution




(b) Ordered distribution



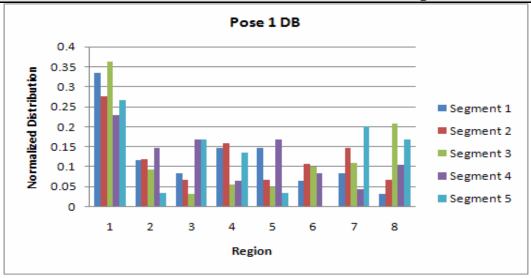

(c) Original Graph




(d) Re-ordered Graph

**Fig. 5.** Segment 1: Multi layers of 2D appearance, the $2^{nd}$ region in (a) has highest number pixel points and re-ordered the sequence as start region ($1^{st}$ region); (b) with clockwise order sequence; (c) Graph of original pixel distribution; (d) Graph of re-ordered distribution based on highest number of pixels

**Table 1.** Hand posture database and re-ordered distribution of 2D graph

<table>
<tr><th>No.</th><th>Pose DB</th><th>Re-ordered Distribution of 2D Graph</th></tr>
<tr><td>1</td><td></td><td>
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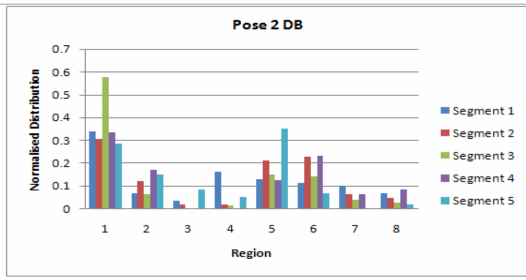
<tr><td>2</td><td></td><td>
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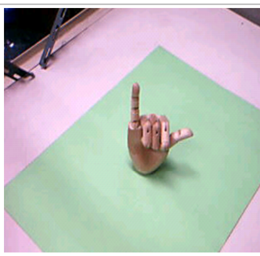
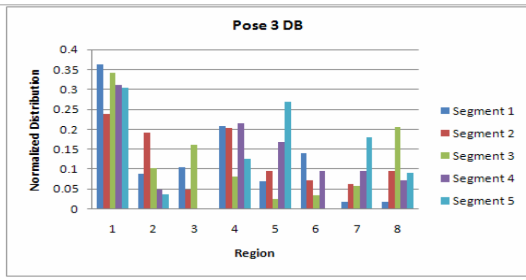
<tr><td>3</td><td></td><td>
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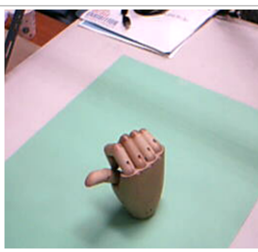
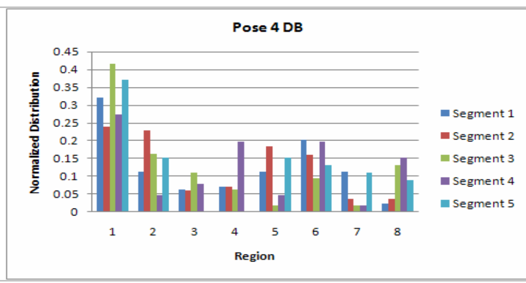
<tr><td>4</td><td></td><td>
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## 5 Experimental Results

In order to validate the proposed method for posture recognition application, artifact hand gestures experiment were carried out. Table 1 shows part of database for hand pose and re-ordered distribution of 2D graph for each pose. The re-ordered distribution of 2D graph shows the pixel points distribution for each region of each segment. The segment is referred to a cylindrical virtual boundary and the 3D voxels of each segment division. For this hand postures experiment, there are total 10 poses are created in database (see Fig. 6). Table 2 shows two examples of test hand pose to recognize the test pose from the defined database.

The matching results for hand test poses recognition are shown in Fig. 7 and Fig. 8. The Fig. 7 shows the details process of matching the hand pose for pose test 1 within

**Table 2.** Test hand pose and re-ordered distribution of 2D graph

<table>
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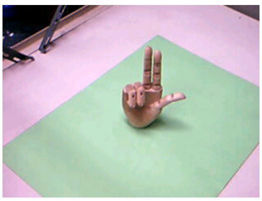
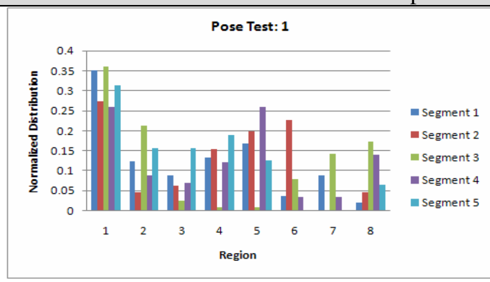
<tr><td>1</td><td></td><td>
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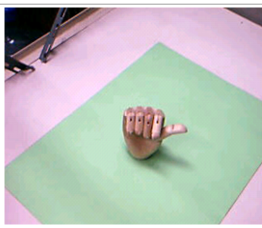
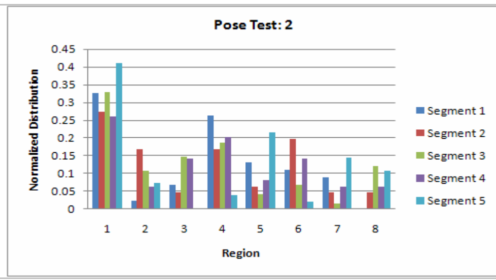
<tr><td>2</td><td></td><td>
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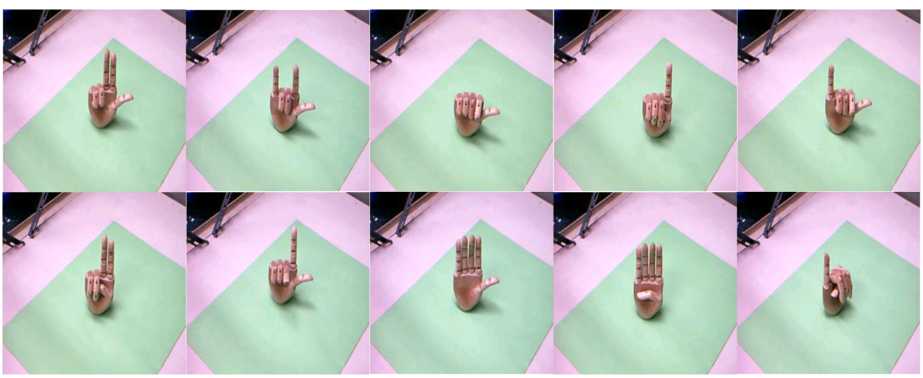

**Fig. 6.** The 10 poses of hand posture are derived in the proposed system database

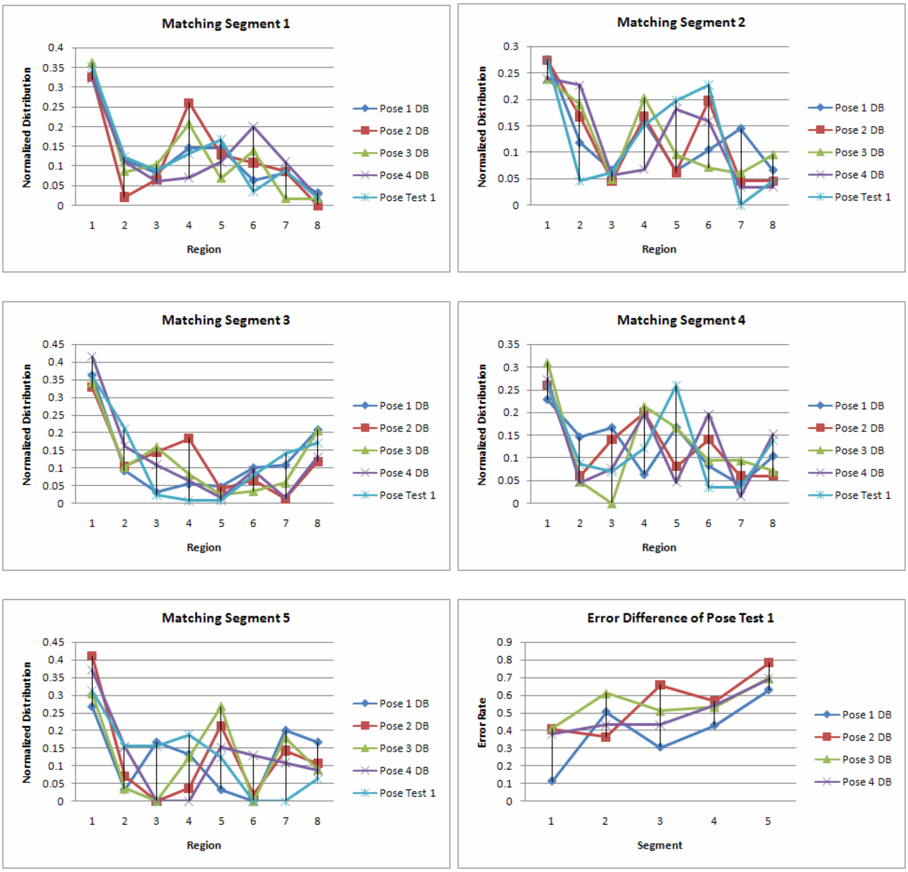


**Fig. 7.** Example of matching process for Pose Test 1 within poses in database: the lowest error difference of Pose Test 1 is Pose 1 DB with 1.983 of total error rates for five segments.

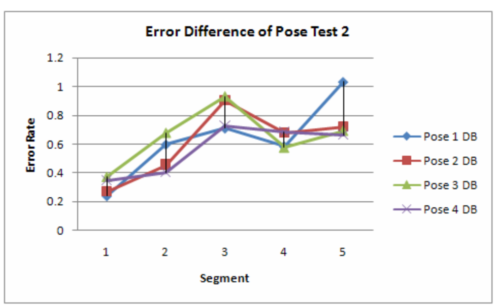


**Fig. 8.** Example of matching process for Pose Test 2 within poses in database: the lowest error difference of Pose Test 2 is Pose 4 DB with 2.819 of total error rates for five segments

each segment from the database. The error difference is computed from 10 poses and the total lowest value of error difference of the pose is matched. The figure shows only four poses of database and the pose test. From the experiment result show that, the pose test 1 is matched with Pose 1 DB with total error difference 1.983. Fig. 8 shows another experimental result of pose test 2 data with four poses from the database. The matched result is Pose 4 DB with lowest total error difference is 2.819. This experimental results show the matching process of the 3D hand posture using the multi layers of 2D appearance is reasonable and simple approach for posture recognition application.

## 6 Conclusions and Future Work

This paper presented dimension reduction method using meshless parameterization with cylindrical virtual boundary for 3D posture representation. This method provides posture modeling in multi layers of 2D appearance representation for 3D posture. The results of meshless parameterization with cylindrical virtual boundary overcome the inconsistency of boundary shape of 3D posture and it is also easy to identify the starting position on 2D domain for matching purpose. The experimental results show the proposed system is possible to recognize posture using matching method at reasonable performance. The 2D representation graph with the lowest total error difference matching rate is recognized as candidate posture from the database. Moreover, the system is good enough and simple to implement for recognizing the 3D posture easily.

As for the future work, we will continue to study and upgrade the system in order to recognize human hand posture and a series of 3D temporal gesture data. We intend to make this algorithm to extract the specific features of each pose automatically. We also plan to evaluate the performance of recognition using specific features for each posture based on the multi layers of 2D appearance.

**Acknowledgments.** This work was supported by the Soongsil University Research Fund.

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