行政院國家科學委員會專題研究計畫 成果報告

整合三維頻率特徵及相關與非相關模型之自動選擇機制於 3D 模型檢索系統
研究成果報告(精簡版)

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摘要

關鍵詞：密度三維ART，三維小曲率轉換，三維傅立葉轉換

　　隨著電腦技術發展的日新月異，人類越來越想在電腦上模擬出真實世界的物體，而不僅僅只是單純的相片、影像。也因為發展3D模型的工具和掃描技術的大幅發展，如AutoCAD、3D Studio、Maya等開發軟體，使3D模型的製做變得相當容易。而網路的快速發展也功不可沒，它加速了資料的流通與獲取的管道。以前，往往只有機械工程師、動畫師等專業人士才能接觸到大量的3D模型。所以在本計劃中，我們先結合Grid-based Principal Components Analysis (GPCA),Continuous Principal Component Analysis (CPCA)和PCA on the normals of the model's faces (NPCA)，將3D模型擺正，避免3D模型旋轉時所造成的誤差，接著結合了密度3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換(3D-Discrete Curvelet Transform, 3D-DCT)和三維傅立葉轉換(3D-Discrete Fourier Transform, 3D-DFT)來擷取特徵，更詳細的描述模型的特徵。

一. 報告內容

1. 前言

　　近年來，3D風潮如同旱地驚雷般地在所有領域颳起一陣旋風，諸如遊戲、動畫、網路、機械、娛樂等，大量的 3D 模型應運而生。面對現今數量龐大的 3D 模型資料庫，在搜尋上將產生相當大的問題。在過去，傳統的關鍵字搜尋方式不僅不直覺，且隨著每個人主觀的分類不同，往往不能滿足我們在 3D 模型萃取上的需求。因此，如何有效率地搜尋出使用者所期望的 3D 模型，儼然成為目前重要的研究課題。因此在本計劃中，我們藉由擷取 3D 模型的表面曲率來加強表示出模型中的外部資訊，所以我們在本計劃是先結合 Grid-based Principal Components Analysis (GPCA) ,Continuous Principal Component Analysis (CPCA)和 PCA on the normals of the model's faces (NPCA)，將 3D 模型擺正，避免 3D 模型旋轉時所造成的誤差，在結合密度 3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換(3D-Discrete Curvelet Transfo-rm, 3D-DCT)和三維傅立葉轉換(3D-Discrete Fourier Transform, 3D-DFT)來擷取特徵，並對特徵進行比對。

2. 研究目的

　　基於這些外部及內部特徵，我們已可以粗略地描述 3D 模型，但是對於日趨複雜的 3D 模型而言，我們希望能提出更精確的方法去描述它。因此本計畫結合密度 3D-ART、三維小曲率轉換和三維傅立葉轉換擷取 3D 模型的特徵，使得 3D 模型檢索系統能夠更加的完善。

3. 文獻探討

隨著電腦技術的快速發展、電腦運算效能的大幅提升，人類在電腦螢幕的世界裡不再滿足由圖片、影像為主構成的二維平面世界，而積極的追求由3D模型所構成的真實世界。然而，現今製作3D模型的軟硬體操作越來越簡單，因此使用者可以更方便的製作出一個3D模型。也因為製作3D模型趨於簡單化，所以要取得3D的模型也變得更為容易。

近年來，國內外已經有很多學術單位投入3D模型搜尋的研究，在網路上也有好幾個系統供人使用，我們也建立了一個3D模型檢索系統(如圖一)。然而，對於日趨複雜的3D模型而言，只用單用一種特徵擷取的方法是無法對全部的模型都有很好的檢索效果，我們希望能組合多種特徵以達到更好的檢索效果，而且試著對每個查詢模型，找到其最適用的特徵組合。因此如何有效率地針對每一個查詢模型搜尋出使用者所期望的3D模型，儼然成為目前重要的研究課題。
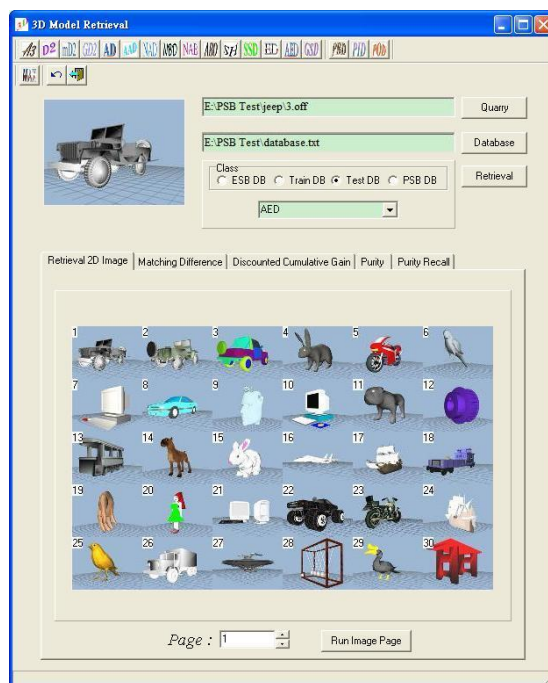

圖一 我們的 3D 模型檢索系統介面。

以下我們將針對國內外有關 3D 模型檢索的相關文獻分成三大類別介紹，分別為頻率特徵(frequency descriptor)、二維投影特徵(2D view feature)和外形特徵(spatial shape descriptor)，最後再針對特徵整合及相關性回饋的相關文獻做介紹。

1)頻率特徵(frequency descriptor)：

Vranic 等人[1] 提出利用球型諧波來計算 3D 模型的特徵向量，但此方法必須先將 3D 模型做 PCA 正規化才不會受旋轉的影響。因此 Funkhouser 等人[2，3] 即提出了即使不需將模型先做正規化也依然可以利用球型諧波公式求出特徵向量。其主要概念是將 3D 模型的資料轉換成頻率(frequency)的表示法，就有如 2D 上的傳立葉轉換(Fourier transform)一般。也就是

對不同半徑的同心球(concentric spheres)中的資料，使用球型諧波來求得 3D 模型的特徵向量，這樣就能避免因旋轉而產生的問題。

　　Zhang 及 Chen [4] 提出一種有效率計算特徵的方法，首先將 3D 模型利用網格(mesh)切割成一小塊一小塊的，而每一小塊就稱為 voxel。每個 voxel 可標為 1 或 0，視 voxel 為落在 3D 模型的內部或外部而定，由此可計算 3D 模型的體積，再利用模型中的三角片(mesh)對 3D 模型取矩量(moments)和富立葉係數來當特徵。如此的觀念也可應用在 PCA 的正規化找尋主軸上(如圖二)，主要是利用對 3D 模型取矩量所得到的一個 3×3 的矩陣，計算出該矩陣的 3 個 eigenvectors，則這些 eigenvectors 即為該 3D 模型的 3 個主軸。
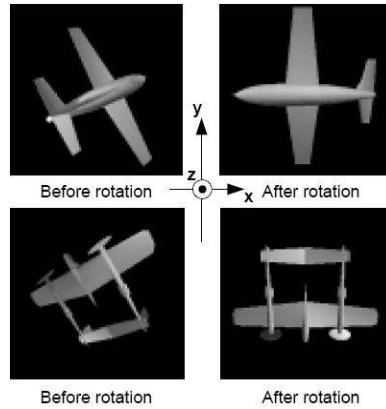
圖二　做 PCA 之前與之後的 3D 模型[4]。

　　Papadakis[5]等人提出基於球型諧波的理論下，使用兩種不同的 3D 模型擺正方法，並將兩種結合為一。而擺正的方法分為，在點座標系統下進行 3D 模型的擺正(CPCA)以及使用該模型上三角片的單位法向量做擺正的動作(NPCA)。做完擺正的動作以後，對於每個 3D 模型的中心點，根據不同的角度可放射出與模型表面形成交集的射線，將交集與中心點之間的線段，等距離補點。再對 CPCA 與 NPCA 兩種擺正方式，利用球型諧波針對已補點完的 3D 模型，進行擷取特徵值的動作。最後，將兩種擺正方法所得到的特徵值組合起來，即為該 3D 模型的特徵值(如圖三)。
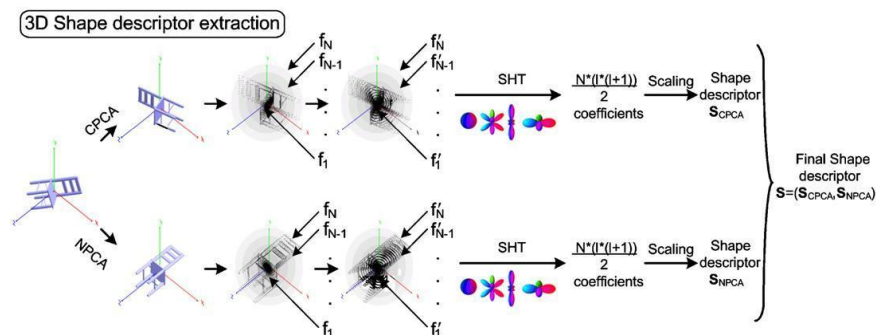

圖三　NPCA 和 CPCA 於特徵擷取和外形比對組合[5]。

2) 二維投影特徵(2D view feature)：

　　此類方法的主要觀念是藉由許多二維黑白影像(binary images)或是灰階影像(gray-level

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images)來描述一個 3D 模型，二維影像可從 3D 模型的邊界輪廓上以不同的視角所取得，然後使用 2D 特徵來進行比對並找尋相似的 3D 模型。以下我們將針對幾個系統來介紹。

以 T. Funkhouser [6]提出之 3D 模型搜尋引擎為例，使用者可以任意畫出一個 3D 形狀(3D Sketch)去 3D 資料庫中做搜尋(如圖四)，或者使用者可利用前視圖、側視圖、以及俯視圖來描繪出一個 3D 形狀，並利用這三張影像來做搜尋，也可以用關鍵字進行搜尋，此類方法多半是使用剪影圖形來進行比對並將比對結果回應給搜尋者。
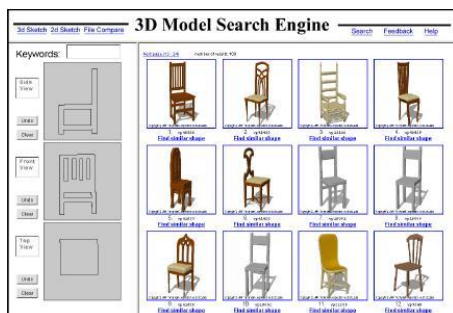
圖四　3D 模型搜尋引擎[6]。

Super and Lu [7] 利用 2D 輪廓剪影來辨識 3D 物件。其先將 3D 物件擺正在 x-y 的平面上，然後將 3D 物件旋轉 16 個角度，每次旋轉角度為 22.5^o。藉此達到環繞整個 3D 模型，因此可取得 16 張 2D 輪廓剪影(如圖五)。最後利用 scale-space 的方法擷取特徵。
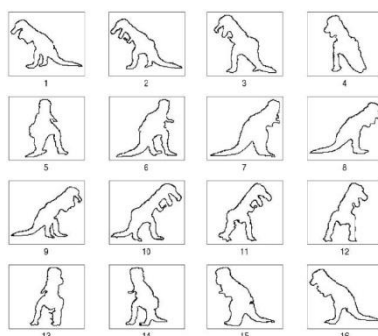
圖五　利用 2D 輪廓剪影來辨識 3D 物件，利用十六個角度看恐龍，每個角度的區間為 22.5^o[7]。

在三維模型的調準與檢索系統（A 3D Model Alignment and Retrieval System）[8]中 Chen 等人[9] 介紹一種光影描述(lightfield descriptor)來搜尋 3D 模型。光影描述特徵的計算是藉由 N 個不同角度觀察所獲得的 N 個剪影，接下來把這些 2D 剪影使用 ART（Angular Radial Transform）擷取 2D 形狀特徵來當作此 3D 模型的特徵向量。

我們在 94 年之國科會計專題研究計畫針對 3D 模型的檢索提出了一個六立面體的方法[10]。此方法已投稿至 Patten Recognition 期刊，已於 2007 年 1 月發表。首先，一個 3D 模型從六個不同的視角，產生六個不同的投影灰階平面(如圖六)，我們稱之為立面圖。灰階值的深淺代表模型在該立面圖的高度分佈資訊。接著將每一個立面利用同心圓擷取特徵，就可以

算出兩個 3D 模型的相似程度。
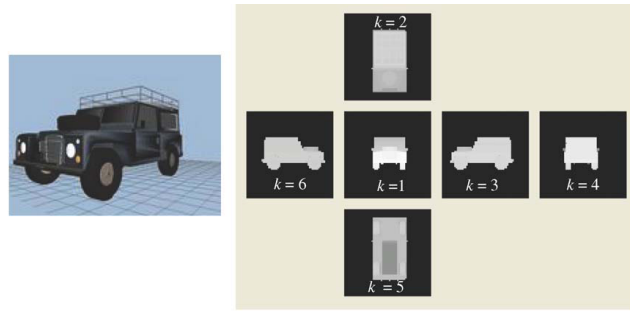
圖六 3D 模型的六個投影立面圖 [10]。

Chen-Tsung Kuo[11]提出了主要平面分析的方法，其目的是要改善傳統主軸分析的方法在兩個相似的 3D 模型上因為外觀的些微差異而導致主軸的偏移。因此，將主軸分析的觀念沿伸至主要平面分析，主平面的判斷是在 3D 模型中所有的點到某個平面距離之合最小，則該平面為 3D 主要平面。

主平面分析的做法是將一個原始 3D 模型(如圖七(a))，將模型上所有的點投影到主要平面使得 3D 模型轉至成 2D 影像(如圖七(b))，最後在此 2D 影像上取特徵。

(a) (b) (c)
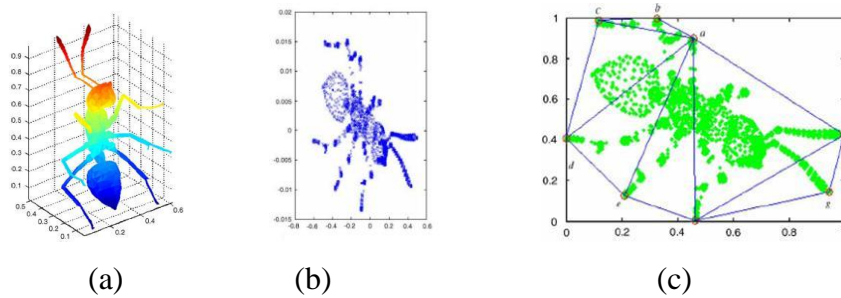
圖七 主平面分析 (a)一個原始螞蟻模型，(b)投影至主平面的 2D 黑白影像，(c)和所切割出來的最佳的三角形區域[11]。

我們在 96 年所提出之國科會專題研究計畫曾針對 3D 模型的檢索提出了將 3D 模型投影到三個主平面的方法[12]。主要的作法為，對於每個 3D 模型，在空間中找到一個平面使得模型上的所有點到平面的距離總合會最小，此平面稱為第一主平面 E_1。根據 E_1 平面，我們可以找出跟 E_1 平面垂直的第二主平面 E_2 及第三主平面 E_3(如圖八(b))。對於每個 3D 模型，投影到三個主平面，可以得到三張黑白影像，再利用同心圓的方式針對三張黑白影像擷取特徵(如圖八(d))。

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(a)   (b)   (c)   (d)
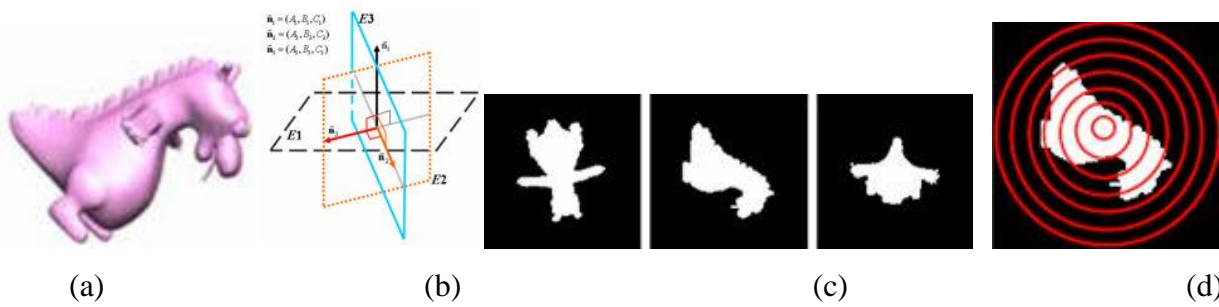
圖八 (a)3D 模型,(b)三個主平面 E_1、E_2 以及 E_3,(c) 3D 模型與投影到三個主平面所得到的黑白影像,(d) 利用同心圓擷取黑白影像的特徵[12]。

Ricard[13]等人提出一個 3D 形狀特徵的描述方法,其主要做法為將 MPEG-7 中所提到的 2D Angular Radial Transform(2D-ART) 轉換到 3D 空間中,首先將每個 3D 模型用球面座標來表示,接下來針對每個 3D 模型沿著 Z 軸方向做 Principal Components Analysis (PCA)的擺正。最後,再做 3D-ART 來擷取特徵向量。
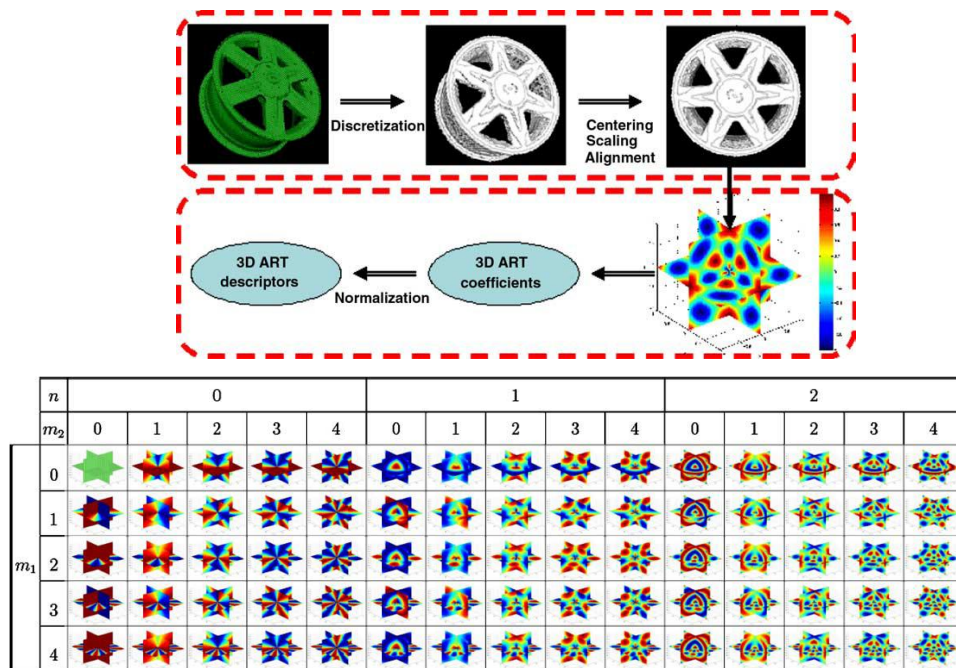
圖九 3D-ART 係數值中的實數部分[13]。

Dimitios Zarpalas[14]等人提出一個 3D 模型檢索系統。主要的做法為將一個 3D 模型切成 128×128×128 個網格,每 8 個 2×2×2 的網格就組合成一個巨型網格(coarser voxel),對於每個 3D 模型,均可切出 64×64×64 個巨型網格(如圖十(a))。在一個正二十面體中,找出通過 3D 模型的中心點且與正二十面體上的十二個頂點形成切線的平面(如圖十(b))。每個平面使用灰階影像來表示,影像中的灰階值代表單一巨型網格中所包含有效網格的數量。而對於每個正二十面體,再分成二十種不同的半徑,因此,對於每個 3D 模型,可用 240(12×20)張灰階影像來表示。

<div align="center">(a)　　　　　　　　　　　　　　　　　　　(b)</div>
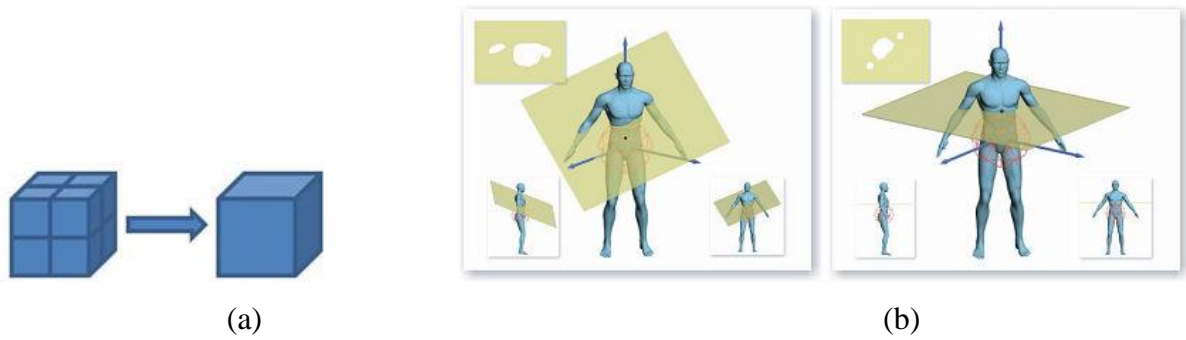
圖十 (a) 8 個小網格合成一個巨型網格,(b)在正二十面體上的十二個頂點中,兩個不同的頂點所形成的切線平面。

Mohamed Chaouch[15]等人提出一個 3D 模型檢索系統,這套系統主要的方法是藉由 3D 模型投影到一個正十二面體的二十個頂點方向如圖十一(a)所示,所得到的二十張深度影像,再對這些深度影像作特徵擷取的動作。對於每張深度影像,根據影像大小(N*N),分別在水平以及垂直方向上劃出 N 條深度線,即每張影像可劃出 2*N 條深度線如圖十一(b)之上半部所示。利用深度線來描述 3D 形狀的邊界輪廓比起其他使用 2D 形狀表示法來的更為精確。最後再將深度線編碼完的序列,使用動態規劃演算法計算出兩個序列的相似度。

Assfalg[16-18]等人提出利用曲率投影進行 3D 模型檢索的方法,主要的做法為先對每個 3D 模型上的三角片做平滑處理(如圖十二)。再對於 3D 模型做變形處理以及曲率投影的動作(如圖十三)。最後利用直方圖即可統計出整張影像的曲率分布資訊。

<div align="center">(a)　　　　　　　　　　　　　　　　　　　(b)</div>
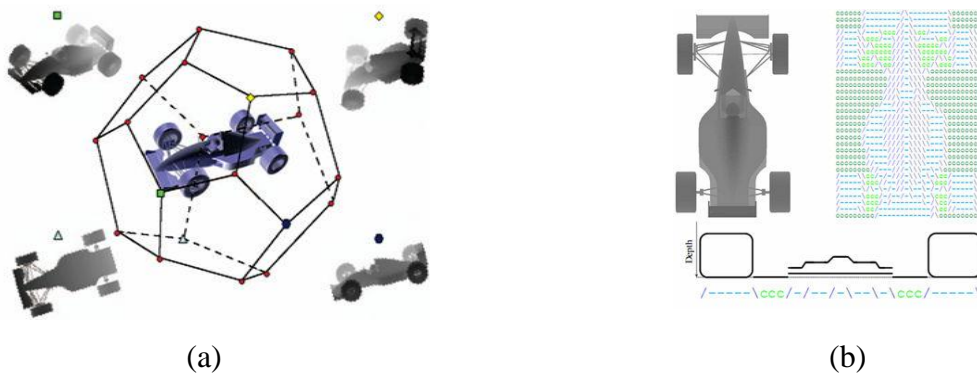
圖十一 (a) 從不同的角度所投影出來的深度影像。(b) 賽車影像的深度線[15]。
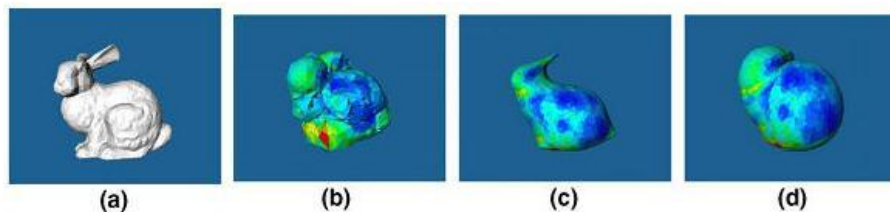
圖十二 3D 模型做平滑處理的過程,(a)原來的 3D 模型,(b)做 Laplacian 運算,(c)做 Gaussian 運算,(d)結合 Laplacian 與 Gaussian 運算[16]。

(a)	(b)
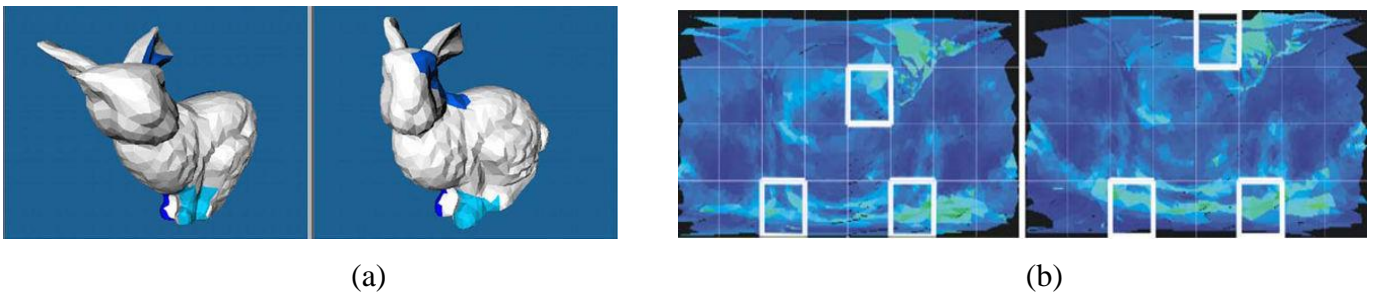
圖十三　(a)兩個相似的 3D 模型。(b)曲率投影所得到的影像以及三個最相近的區塊[16]。

　　You-Shin Park et al. [19]提出一個基於主軸分析法(PCA)的 3D 模型檢索系統。這方法的主要想法就是，分別沿著 PCA 所得到的三個主軸，各自產生 2D 切片圖形影像的直方圖，並當作形狀特徵，比較各個 3D 模型的直方圖進行測量相似度。對於每一個 3D 模型，三個主軸等分切割出一百個垂直於主軸的平面，切出來的每一個平面是貫穿 3D 模型所產生的 2D 形狀切片(sliced shape)影像(如圖十四(b))，而這些 2D 片影像就是具有 3D 模型橫切面輪廓。計算每一個 2D 影像的中心點到橫切面輪廓的距離(如圖十四(c))並統計成直方圖，組合同一個主軸的一百個直方圖成為一個新的特徵向量，最後可以分別獲得三個主軸的切片直方圖特徵(sliced histogram descriptor)來做相似度測量(如圖十四(d))。

(a)	(b)	(c)	(d)
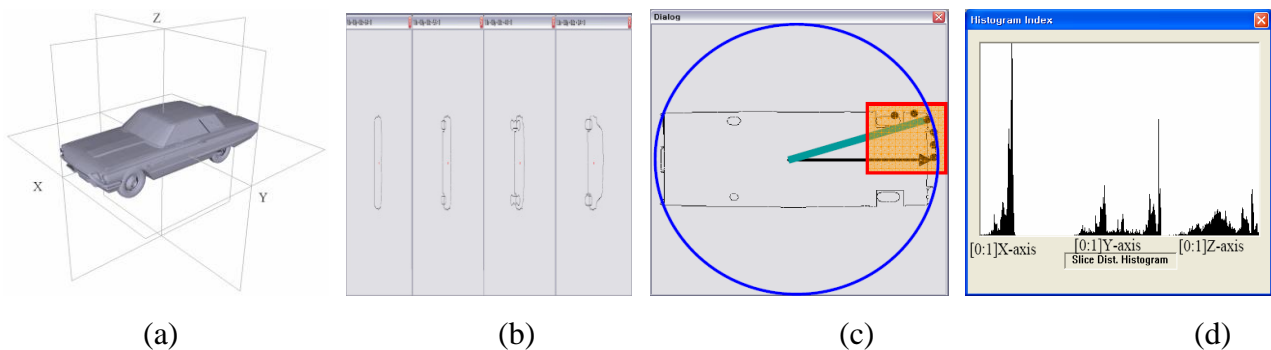
圖十四　(a) 以三個主軸分別產生的三個平面方程式。(b) 3D 汽車模型 x 軸的 2D 形狀切片。(c) 計算原點到外形的距離。(d) 從三個主軸分別獲得的切片直方圖特徵[19]。

3) 形狀特徵(spatial shape descriptor)：

　　Osada et al. [20,21] 提出 3D 幾何形狀分佈 (3D shape distributions) 的方法。這幾何形狀函式(shape function)有下列五種，A3、D1、D2、D3、D4(如圖十五)，分別代表意思為：A3，在 3D 模型上亂數任取三個點所產生夾的角度。D1，固定中心點並在模型邊緣上亂數選取的點，藉由固定點和選取點計算兩點間距離。D2，在 3D 模型邊緣上亂數選取任兩點並計算出兩點之間的距離。D3，亂數選取三點形成面積並計算面積。D4，亂數選取四點形成體積並計算體積。其中 D2 為最常用之方法。
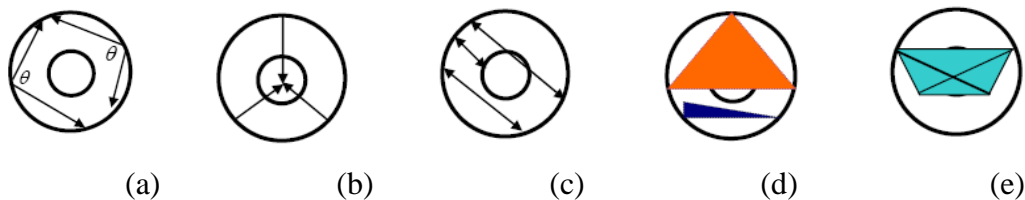
圖十五　函式圖形(a) A3 (b) D1 (c) D2 (d) D3 (e) D4[20,21]。

　　MPEG-7 中擷取 3D 模型特徵的方法,其主要做法先把 3D 模型解析度統一為計算模型上的每個面的曲率,然後統計每種曲率出現的頻率做成直方圖(histogram)當作檢索時之特徵向量。其主要步驟介紹如下:先利用表面平滑細分演算法(Smooth Subdivision Surfaces)[22]。接下來計算每一個平面的曲率(curvature),及其平均法向量(mean normal vector)。如此可求出該模型的形狀索引(shape index)。計算出來的形狀索引值會因為曲面的曲率不同而有所改變。例如曲面呈現下凹的半球型的話,則計算出來的形狀所以會趨近於 0;曲面呈現上凸的半球型的話,則計算出來的形狀會趨近於 1(如圖十六)。根據這些形狀索引,我們將可以詳細的描述 3D 模型的外型。
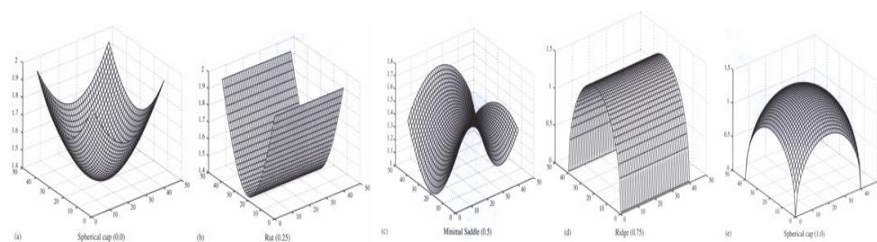
圖十六　MPEG-7 中擷取 3D 模型的形狀索引示意圖[23]。

4. 研究方法

　　在過去的3D 模型檢索系統中,常運用Principal Component Analysis(PCA)的方法,求得3D 模型的主軸,並以此擺正模型。傳統的PCA 做法,是利用模型中三角片的頂點座標們來計算主軸(Principal axes),但以圖十七為例,吉普車中的輪胎的部分非常複雜,須要用許多的三角片來表示,如此三角片分佈不均的情況,會造成主軸計算時的偏差。Papadakis[5]提出兩種不同的3D 模型擺正方法,並將兩種結合為一。而擺正的方法分為,在點座標系統下利用三角片面積為權重值來計算主軸(Continuous Principal Component Analysis, CPCA)以及使用該模型上三角片的單位法向量來計算主軸(the PCA on the normals of the model's faces, NPCA)。再對經CPCA與NPCA兩種擺正後的3D 模型,進行擷取特徵值的動作。最後,將兩種擺正方法所得到的特徵值組合起來。

　　　　因此在去年已結案的國科會計畫提出了 Grid-based Principal Components Analysis (GPCA)可把 3D 模型切成網格,去過濾模型的細微變化,也可充分的表現出 3D 模型的外型。

每格網格都只會取得一個特徵參數來計算主軸,不會因為三角片分佈不均的問題來影響主軸的精確度。但是因 3D 模型變化很大,無法用一種擺正的方法去滿足所有的 3D 模型,因此我們在本年度的計畫中結合 Continuous Principal Components Analysis (CPCA)和 Normals Principal Components Analysis (NPCA) ,三種擺正的方法各有優點,利用三種擺正的方法,希望能正確地擺正大部分的模型(如圖十八)。觀念如下:

假設查詢模型經三種擺正方式擺正後,分別求得之特徵向量如下:

$$S^Q = \left(S^Q_{GPCA}, S^Q_{CPCA}, S^Q_{NPCA}\right),$$

在資料庫的比對模型也經三種擺正方式擺正後,分別求得之特徵向量如下:

$$S^{DB} = \left(S^{DB}_{GPCA}, S^{DB}_{CPCA}, S^{DB}_{NPCA}\right),$$

在兩兩比對之後,取之間最小的來當作最合適的擺正模型。

$$D\left(S^Q, S^{DB}\right) = \min\left\{L_1\left(S^Q_{GPCA}, S^{DB}_{GPCA}\right), L_1\left(S^Q_{CPCA}, S^{DB}_{CPCA}\right), L_1\left(S^Q_{NPCA}, S^{DB}_{NPCA}\right)\right\}$$

(a)　　　　　　　　　　　(b)
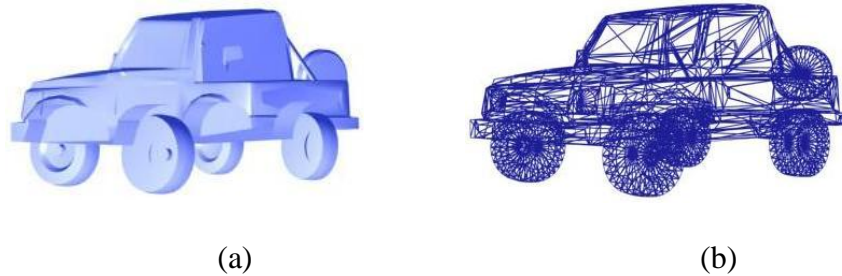
圖十七 (a)吉普車的 3D 模型(b)吉普車的三角片分佈。
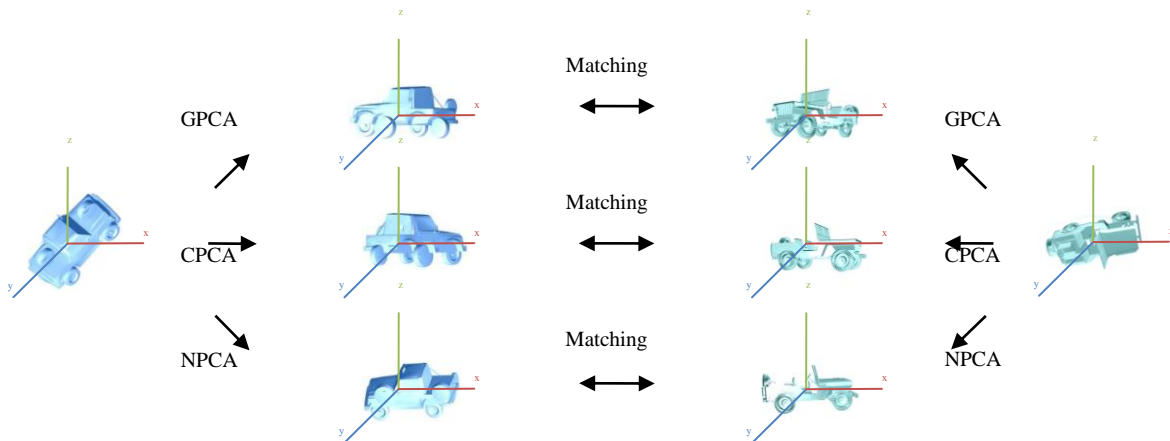
圖十八 GPCA、CPCA 和 NPCA 之間的擺正和比對。

將模型擺正之後,為了不受到模型大小所影響,須對模型大小在正規化一次。將模型切割成 128×128×128 的網格,如圖二十一(b)所示,將 3D 模型的質量中心移動到(64, 64, 64)位置,並縮放 3D 模型讓所有有效網格到達中心的平均距離為 32,如圖十九(c)所示。移動 3D 模型的質量重心到正立方體的中心。

| (a) | (b) | (c) |
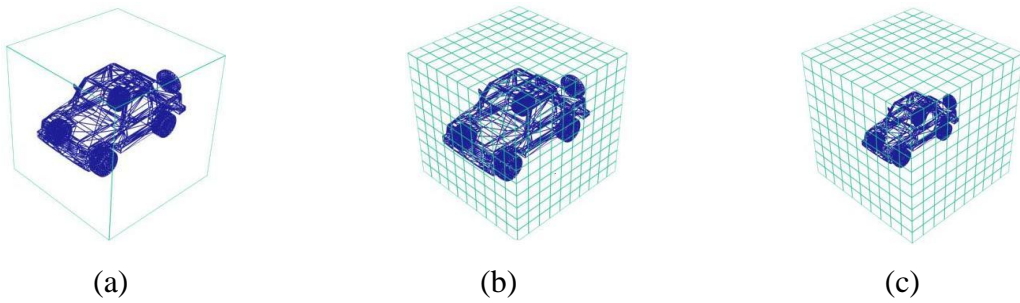
圖十九 對擺正後的 3D 模型做大小的正規化 (a)最小立方體包圍住 3D 模型 (b)正規化 3D 模型前 (c)正規化 3D 模型後。

針對頻率特徵，我們希望整合三種方法：

    （1）密度 3D-ART(Density 3D-ART Descriptor)。

    （2）3D 小曲率轉換(3D Discrete Curvelet Transform)。

    （3）3D 傅立葉轉換(3D Fourier Transform)。

（1） 密度3D-ART(Density 3D-ART Descriptor)：

    在這次計畫中的密度 3D-ART 特徵(Density 3D-ART Descriptor)是針對原本的 3D-ART[13] 做改善。主要作法為將一個 3D 模型切成 128×128×128 的網格,如圖二十一所示,每 8 個 2×2×2 的微型網格(tiny voxel)就組合成一個巨型網格(coarser voxel)，如圖二十所示，對於每個 3D 模型，均可切出 64×64×64 個巨型網格，如圖二十(b)所示。在每格微型網格中若有 3D 模型多邊型的面存在就將此網格視為 1，$TinyVoxel(x,y,z) = 1$，(代表此微型網格為有效網格)；反之微型網格中沒有 3D 模型存在則將它視為 0，$TinyVoxel(x,y,z) = 0$，(代表此微型網格為無效網格)。每個巨型網格中有效微型網格的個數，即為這巨型網格的代表值，範圍為[0 ~ 8]。

| (a) | (b) |

圖二十 3D 模型 (a)切成 128×128×128 的微型網格 (b)每 2×2×2 的微型網格,合併成一個巨型網格，形成 64×64×64 的巨型網格。
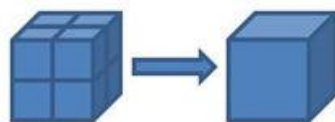
圖二十一 2×2×2 的微型網格,合併成一個巨型網格。

對應的密度 3D-ART 係數 $F\left(n, m_{,\theta}\, m_{\varphi}\right)$ 定義如下：

$$F\left(n, m_\theta\, m_\varphi\right) = \int_0^{2\pi}\int_0^\pi\int_0^1 V_{n,m,\theta\,m_\varphi}^*\left(\rho,\theta,\varphi\right)f\left(\rho,\theta,\varphi\right)\rho d\rho d\theta d\varphi$$

$f(\rho,\theta,\varphi)$ 為極座標上的強度，$V_{nm_\theta m_\varphi}(\rho,\theta,\varphi)$ 是密度 3D-ART 特徵的基底函式。基底函式是由兩個角度以及一個徑度。

$$V_{nm_\theta m_\varphi}\left(\rho,\theta,\varphi\right) = A_{m_\theta}(\theta)A_{m_\varphi}(\varphi)R_n(\rho).$$

角度和徑度的基底函式分別定義如下：

$$A_{m\theta}\left(\theta\right) = \frac{1}{2\pi}\exp\left(2jm_\theta\theta\right)$$

$$A_{m_\varphi}\left(\varphi\right) = \frac{1}{2\pi}\exp\left(2jm_\varphi\varphi\right)$$

$$R_n\left(\rho\right) = \begin{cases} 1 & ,n=0 \\ 2\,\mathrm{c\,o}(\mathfrak{s}n\pi\rho), n \neq 0 \end{cases}$$

根據密度 3D-ART 特徵轉換得到 γ 組係數，其中 $\left|F\left(n, m_\theta, m_\varphi\right)\right|$ 是介於 $0 \leq n \leq 2$，$0 \leq m_\theta \leq 4$ 且 $0 \leq m_\varphi \leq 4$（除了 $n=0, m_\theta=0, m_\varphi=0$ 之外），最後密度 3D-ART 特徵定義如下：

$$\mathbf{vt}^{3D-ART} = [vt^{3D-ART}(1), vt^{3D-ART}(2),\ldots,vt^{3D-ART}(\gamma)]^\mathrm{T}$$

圖二十二　密度3D-ART的基底函式。

密度3D-ART特徵相似度比對：

　　這裡介紹密度3D-ART特徵的相似度比對。$\mathbf{v}^{3D-ART}$ 和 $\mathbf{u}^{3D-ART}$ 分別表示為密度3D-ART特徵中的查詢模型q和比對模型t的特徵向量。查詢模型和比對模型之間的距離就定義如下：

$$Dis_{q,t}^{3D-ART,\gamma} = \sum_{k=1}^{\gamma}\left|v^{3D-ART}(k) - u^{3D-ART}(k)\right|$$

(2) 3D小曲率轉換特徵擷取：

　　我們也希望能將3D小曲率轉換(3D Discrete Curvele Transform)[23,28]應用於3D模型檢索，對一個3D模型 $f(x,y,z)$ 做3D小曲率轉換後對應的係數 $C^D(j,l,k)$ 將被做為第二組特徵，定義如下：

$$C^D(j,l,k) := \sum_{n_1,n_2,n_3} f(x,y,z)\overline{\varphi_{j,l,k}^D(x,y,z)}.$$

其中 j, $l \in Z$, $k = (k_1, k_2, k_3)$, j 為長度、l 為角度方向、k 為空間座標、$f(x,y,z)$ 為3D模型，範圍在, $0 \le x$, y, $z \le n$。而基底函式 $\varphi^D_{j,l,k}$ 依 j 的位置被分成三種等級：

第一種用在內圈，切割網格較粗時 $(j = j_0)$，經由傅立葉轉換所獲得的基底函式計算如下：

$$\hat{\varphi}^D_{j_0,0,k}(\omega) = \frac{\tilde{U}_{j_0,0}(\omega)}{\sqrt{L_{1,j_0} \cdot L_{2,j_0} \cdot L_{3,j_0}}} \cdot \exp[-2\pi i(k_1\omega_1 / L_{1,j_0} + k_2\omega_2 / L_{2,j_0} + k_3\omega_3 / L_{3,j_0})]$$

其中 $0 \le k_1 < L_{1,j_0}, 0 \le k_2 < L_{2,j_0}$, $0 \le k_3 < L_{3,j_0}$。頻率視窗（frequency window）$\tilde{U}_{j_0,0}$，其定義如下：

$$\tilde{U}_{j_0,0}(\omega) = \tilde{W}_{j0}(\omega).$$

笛卡兒環狀（Cartesian coronae）$\tilde{W}_{j0}(\omega)$，其定義如下：

$$\tilde{W}_{j_0}(\omega) = \Phi_{j_0}(\omega).$$

其中 $\Phi_j(\omega_1, \omega_2, \omega_3) = \phi(2^{-j}\omega_1) \cdot \phi(2^{-j}\omega_2) \cdot \phi(2^{-j}\omega_3)$.

第二種用在外圈，切割網格較細時 $(j_0 < j < j_e)$ 經由傅立葉轉換所獲得的基底函式計算如下：

$$\hat{\varphi}^D_{j,l,k}(\omega) = \frac{\tilde{U}_{j,l}(\omega)}{\sqrt{L_{1,j,l} \cdot L_{2,j,l} \cdot L_{3,j,l}}} \cdot \exp[-2\pi i(k_1\omega_1 / L_{1,j,l} + k_2\omega_2 / L_{2,j,l} + k_3\omega_3 / L_{3,j,l})].$$

其中 $0 \le k_1 < L_{1,j,l}, 0 \le k_2 < L_{2,j,l}, 0 \le k_3 < L_{3,j,l}$。頻率視窗（frequency window）$\tilde{U}_{j,l}$，定義如下：

$$\tilde{U}_{j,l}(\omega) = \tilde{W}_j(\omega) \cdot \tilde{V}_{j,l}(\omega).$$

在 l 角度方向，$(1, \alpha_l, \beta_l)$ 為在立方體中心線的方向的楔形立方體（wedge），如圖二十三(b)，角視窗（angular window）$\tilde{V}_{j,l}(\omega)$ 計算如下：

$$\tilde{V}_{j,l}(\omega) = \tilde{V}\left(2^{j/2} \cdot \frac{\omega_2 - \alpha_l \cdot \omega_1}{\omega_1}\right) \cdot \tilde{V}\left(2^{j/2} \cdot \frac{\omega_3 - \alpha_l \cdot \omega_1}{\omega_1}\right)$$

笛卡兒環狀（Cartesian coronae）$\tilde{W}_j(\omega)$，則定義如下：

$$\tilde{W}_j(\omega) = \sqrt{\Phi^2_{j+1(\omega)} - \Phi^2_j(\omega)}.$$

其中 $\Phi_j(\omega_1, \omega_2, \omega_3) = \phi(2^{-j}\omega_1) \cdot \phi(2^{-j}\omega_2) \cdot \phi(2^{-j}\omega_3)$.

最後一種為用在最外圈時 $(j = j_e = \log_2(n/2))$ 經由傅立葉轉換所獲得的底函式計算如下：

$$\hat{\varphi}^D_{j,0,k}(\omega) = \frac{\tilde{U}_{j_e,0}(\omega)}{\sqrt{L_{1,j_e} \cdot L_{2,j_e} \cdot L_{3,j_e}}} \cdot \exp[-2\pi i(k_1\omega_1 / L_{1,j_e} + k_2\omega_2 / L_{2,j_e} + k_3\omega_3 / L_{3,j_e})].$$

且 $L_{1,j_e} = L_{2,j_e} = L_{3,j_e} = n$ 和 $0 \le k_1$, k_2, $k_3 \le n$。頻率視窗（frequency window）$\tilde{U}_{j_e,0}$ 定義如下：

$$\tilde{U}_{j_e,0}(\omega) = \tilde{W}_{j_e}(\omega).$$

笛卡兒環狀(Cartesian coronae)$\tilde{W}_{j_e}(\omega)$，其定義如下：

$$\tilde{W}_{j_e}(\omega) = \Phi_{j_e}(\omega).$$

其中 $\Phi_j(\omega_1,\omega_2,\omega_3) = \phi(2^{-j}\omega_1)\cdot\phi(2^{-j}\omega_2)\cdot\phi(2^{-j}\omega_3)$.
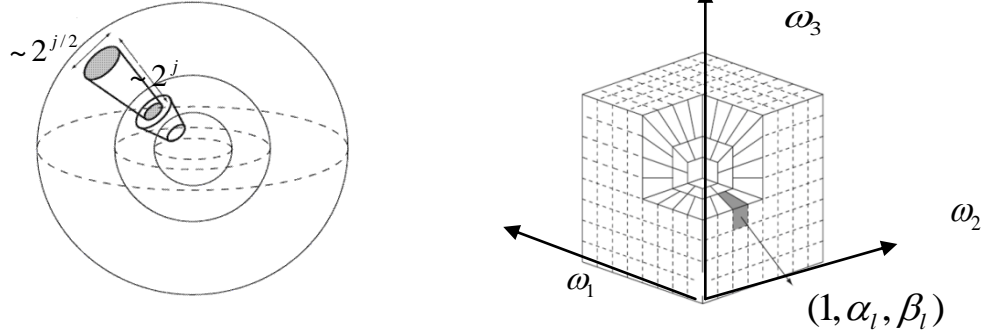
圖二十三 3D小曲率轉換(a)3D小曲率切割示意圖(b)$(1,\alpha_l,\beta_l)$為在立方體中心線的方向的楔形立方體(wedge)，頻率域的方向立方體三軸分別為 ω_1，ω_2，ω_3。

根據3D-DCT特徵轉換得到 κ 組係數，其中 $C^D(j,l,k)$ 是介於

$-3 \le k < 3$，$-\pi\cdot2^{-3} \le l \le \pi\cdot2^{-3}$ 且 $-6 \le j < 6$（除了 $C^D(0,0,0)$），最後3D-DCT特徵定義如下：

$$vt^{3D-DCT} = [vt^{3D-DCT}(1), vt^{3D-DCT}(2),...,vt^{3D-DCT}(\kappa)]^T$$

3D小曲率轉換特徵相似度比對：

這裡介紹3D小曲率轉換的相似度比對。$\mathbf{v}^{3D\text{-}DCT}$ 和 $\mathbf{u}^{3D\text{-}DCT}$ 分別表示為3D小曲率轉換特徵中的查詢模型q和比對模型t的特徵向量。查詢模型和比對模型之間的距離就定義如下：

$$Dis_{q,t}^{3D-DCT} = \sum_{k=1}^{K}\left|v^{3D-DCT}(k) - u^{3D-DCT}(k)\right|$$

（3）3D傅立葉轉換特徵擷取：

3D-DFT公式：

$$g(u,v,w) = \frac{1}{\sqrt{N^3}}\sum_{i=-\frac{N}{2}}^{\frac{N}{2}-1}\sum_{k=-\frac{N}{2}}^{\frac{N}{2}-1}\sum_{l=-\frac{N}{2}}^{\frac{N}{2}-1}f(x,y,z)\exp\left(-j\frac{2\pi}{N}(iu+kv+lw)\right)$$

經由轉換輸出為 G：

$$G = \{g(u,v,w)|g(u,v,w)\in C, -N/2 \le u,v,w < N/2\}$$

Q 是所有像素(Voxel)的集合。把集合 Q 轉經由3D Discrete Fourier Transform(3D-DFT)轉換成集合 G。輸入為 Q：

$$Q = \{q(i,k,l) \,|\, q(i,k,l) \in R, -N/2 \le i,k,l < N/2\}$$

經過轉換，發現係數 $g(u,v,w)$ 的絕對值中指數範圍 $-K \le u,v,w \le K$（指的是最小頻率）。除了係數 $g(0,0,0)$，其他選定的複數都共軛成對。因此，特徵向量由 $((2K+1)^3 + 1)/2$ 的實數所組成。藉由3D-DFT，要獲得較精準的模型空間數值，必須參數 N 值要夠大（也就是選定的立體像素）。

根據 3D-DFT 特徵轉換得到 χ 組係數，其中 $g(u,v,w)$ 是介於 $-2 \le u,v,w < 2$（除了 $g(0,0,0)$），最後3D-DFT特徵定義如下：

$$vt^{3D-DFT} = [vt^{3D-DFT}(1), vt^{3D-DFT}(2), ..., vt^{3D-DFT}(\chi)]^T$$

3D傅立葉轉換特徵相似度比對：

這裡介紹3D傅立葉轉換的相似度比對。$\mathbf{v}^{3D\text{-}DFT}$ 和 $\mathbf{u}^{3D\text{-}DFT}$ 分別表示為3D傅立葉轉換特徵中的查詢模型q和比對模型t的特徵向量。查詢模型和比對模型之間的距離就定義如下：

$$Dis_{q,t}^{3D-DFT} = \sum_{k=1}^{\chi} \left| v^{3D-DFT}(k) - u^{3D-DFT}(k) \right|$$

5. 結果與討論

實驗中我們採用資的料庫是「普林斯頓資料庫（Princeton Shape Benchmark）」[24]，如圖二十四、二十五，此資料庫是提供給對 3D 模型檢索研究有需求的使用者免費使用，大部分的 3D 模型特徵擷取都有用此資料庫來做檢索研究。普林斯頓資料庫含有 1814 個 3D 模型，包含 161 個不同的類別。分成 907 訓練模型(90 個類別)以及 907 測試模型(92 個類別)，如表一所示。

實驗是將我們所提出三種 3D 模型特徵，密度 3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換（3D-Discrete Curvelet Transfom, 3D-DCT）和三維傅立葉轉換（3D-Discrete Fourier Transform, 3D-DFT)和把三種特徵合併後於資料庫中做檢索。表二為三種不同特徵和合併後的特徵於普林斯頓大學 3D 模型資料庫檢索正確率。表三為其他特徵 shell grid descriptor(SGD)[25]、Grid D2(GD2)[26]、Beta/distance histogram(BD)[28]、Extended Gaussian images(EGI) [30]、depth buffer image(DBI) [33]、density-based framework(DBF) [29]、concrete radicalized spherical projection(CRSP)[31]、spherical harmonic representation of the Gaussian Euclidean distance transform(SH-GEDT)[32]、light-field descriptor(LFD)[9]、hybrid descriptor of DBI, SIL, and Ray-Based spherical harmonic(DSR)[33]、spherical wavelet descriptor(SWD)[34]、rotation invariant spherical harmonic(RISH)[32]、shape histograms(SHIST)[35]、silhouette based feature vector(SIL)[33]、3D Hough transform(3DHT)[36]、cord and angle histogram(CAH)[37]、

radicalized extent function(REXT)[38]和 adaptive views clustering(AVC)[39]於普林斯頓大學 3D 模型資料庫檢索正確率。

　　根據資料庫中每個類別的3D模型數量不一樣，實驗裡使用的量測標準為DCG(Discounted Cumulative Gain，DCG)[29]，定義如下：

$$
DCG_k = \begin{cases} DCG_{k-1} + \dfrac{L_k}{\log(k)}, & k \geq 2 \\ L_1, & k = 1 \end{cases}
$$

其中當第 k 個檢索模型與查詢模型來自同一個類別，則 $L_k = 1$，反之 $L_k = 0$ 而查詢模型 q 整體的 DCG 定義為 $DCG_{k_{max}}$，，其中 $k_{max} = N_s$ 是資料庫中模型的總數，從 DCG 的定義來看，當跟模型在相同類別的比對模型排名總是在前頭時，將會獲得一個較大的 DCG 值，如圖二十六。

　　從實驗結果我們發現這個計畫中所實驗之三種內部特徵，密度 3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換（3D-Discrete Curvelet Transfom, 3D-DCT）和三維傅立葉轉換（3D-Discrete Fourier Transform, 3D-DFT)的個別正確率都高於以往 3D 模型常用之三種內部特徵 shell grid descriptor(SGD)[25]、Grid D2(GD2)[26]、Beta/distance histogram(BD)[28]等內部特徵。如果再將此三種內部特徵密度 3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換（3D-Discrete Curvelet Transfom, 3D-DCT）和三維傅立葉轉換（3D-Discrete Fourier Transform, 3D-DFT)合併，則可更進一步將 DCG 提高至 70.16%。未來我們將可把這些新的內部特徵與過去正確率較高之外部特徵如 ART-based elevation descriptor (AED)[25]與 principal plane descriptor (PPD)[12]等合併，去提升整個 3D 模型檢索系統之正確率。

三. 計畫成果自評

　　本計劃中我們提出了三種內部特徵，密度 3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換（3D-Discrete Curvelet Transfom, 3D-DCT）和三維傅立葉轉換（3D-Discrete Fourier Transform, 3D-DFT)，並加以合併，檢索完結果發現合併後新的內部特徵超越了其他內部特徵 shell grid descriptor(SGD)[25]、Grid D2(GD2)[26]、Beta/distance histogram(BD)[28]的正確率，未來我們將可把這些新的內部特徵與過去正確率較高之外部特徵如 ART-based elevation descriptor (AED)[25]與 principal plane descriptor (PPD)[12]等合併，去提升整個 3D 模型檢索系統之正確率。

圖二十四　普林斯頓資料庫中的模型類別。

圖二十五　普林斯頓資料庫中直升機類別的模型。
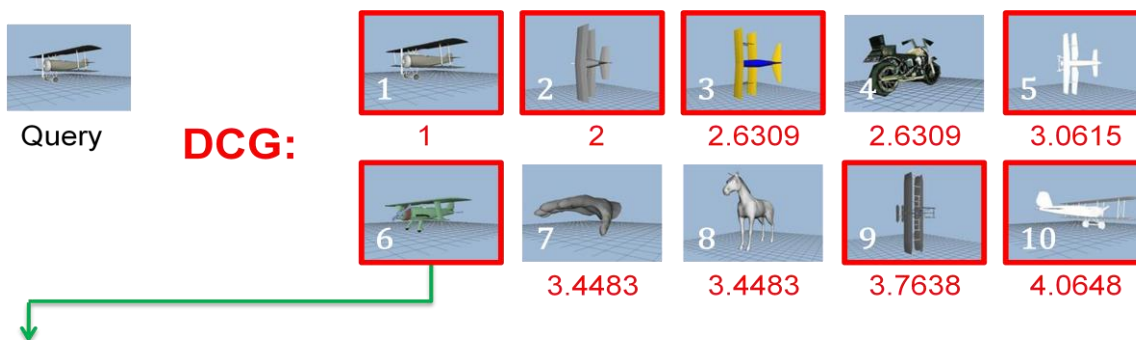
$$\text{DCG}_k = \text{DCG}_{k-1} + \frac{L_k}{\log_2(k)} \quad \Longrightarrow \quad \text{DCG}_6 = \text{DCG}_5 + \frac{1}{\log_2(6)} = 3.0615+0.3865$$

$$\text{DCG}_6 = 3.4483 \qquad\qquad \text{DCG}_{q1} = DCG_1 + \cdots\cdots + DCG_{907} = 6.367868$$

圖二十六　DCG5 值計算之範例解說。

表一 普林斯頓資料庫內 92 個不同類別模型，|Nc|表示類別裡模型的個數。

Category name	|Nc|	Category name	|Nc|	Category name	|Nc|	Category name	|Nc|
Biplane	14	Book	4	Vase	11	Flying_bird	14
Commercial	11	Barn	5	Mailbox	7	School_desk	4
Fighter_jet	50	Church	4	Electrical_guitar	13	Staircase	7
Glider	19	Gazebo	5	Newtonian_toy	4	Standing_bird	7
Stealth_bomber	5	One_story_home	14	Bush	9	Bench	11
Hot_air_balloon	9	Skyscraper	5	Flowers	4	Hammer	4
Helicopter	18	One_peak_tent	4	Potted_plant	26	Dog	7
Enterprise_like	11	Two_story_home	10	Barren	11	Dining_chair	11
Flying_saucer	13	Chess_set	9	Conical	10	Shovel	6
Satellite	7	City	10	Satellite_dish	4	Horse	6
Tie_fighter	5	Desktop	11	Large_sail_boat	6	Desk_chair	15
Ant	5	Computer_monitor	13	Ship	11	Umbrella	6
Butterfly	7	Door	18	Submarine	9	Rabbit	4
Human	50	Eyeglasses	7	Billboard	4	Shelves	13
Human_arms_out	20	Fireplace	6	Sink	4	Race_car	14
Walking	8	Cabinet	9	Slot_machine	4	Snake	4
Rectangular	25	Sedan	10	Fish	17	Single_leg	6
Covered_wagon	5	Sea_turtle	6	Geographic_map	12	Motorcycle	6
Axe	4	Handgun	10	Monster_tuck	5	Knife	7
Hat	6	Semi	7	Sword	16	Hourglass	6
Jeep	5	Face	16	Ladder	4	Train_car	5
Hand	17	Streetlight	8	Wheel	4	Head	16
Glass_with_stem	9	Gear	9	Skull	6	Pail	4

表二 在本計畫所提出之特徵在普林斯頓資料庫正確率比較結果

特徵	DCG(%)
密度 3D-ART	64.18
3D-Fourier	64.05
3D-Curvelet	65.32
合併三種特徵	**70.16**

表三 在其他特徵在普林斯頓資料庫正確率比較結果，其中有標記*的是引用 Akgule [29] 論文中的數據。

特徵	DCG(%)
AED[25]	71.83
SGD[25]	58.65
PPD[12]	65.62
GD2[26]	61.34
BD[28]	58.70
EGI[30]	43.80
CRSF[31]	66.80
LF[9]	64.30
SH-GEDT[32]	58.40
DBI[33]*	66.30
DSR[33]*	66.50
DBF[29]	65.90
DSR+DBF[29]	70.20
SWD[34]*	65.40
RISH[32]*	58.40
SHIST[35]*	54.50
SIL[33]*	59.70
3DHT[36]*	57.70
CAH[37]*	43.30
REXT[38]*	60.10
AVC[39]	60.20

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行政院國家科學委員會補助國內專家學者出席國際學術會議報告

附件三

報告人姓名	周智勳	服務機構及職稱	中華大學資訊工程系
會議 時間 地點	2010/11/4~2010/11/6 日本-福岡	本會核定補助文號	計劃編號： NSC 99-2221-E-216-045-
會議 名稱	（中文） （英文）FIFTH INTERNATIONAL CONFERENCE ON BROADBAND AND WIRELESS COMPUTING, COMMUNICATION AND APPLICATIONS / FIFTH INTERNATIONAL CONFERENCE ON P2P, PARALLEL, GRID, CLOUD AND INTERNET COMPUTING (BWCCA 2010 / 3PGCIC 2010)		
發表 論文 題目	（中文） （英文）A 3D Model Retrieval System Based On The Cylindrical Projection Descriptor		

報告內容應包括下列各項：

一、 參加會議經過

　　　此次會議地點位於日本九州北部的福岡，離台灣不到兩小時的飛行時間，是國人常去的旅遊景點，之前也曾經因為參加會議造訪此地。

　　　我是在會議前一天晚上來到福岡，下榻於福岡 JR 站旁的飯店，飯店有通道直達捷運車站，相當方便。會議地點位於福岡西北方的福岡工業大學，必須搭 JR 線火車前往，還好學校在車站附近，沒有找尋上的困擾。

　　　此次會議有相當多的 workshops 同時進行，session rooms 分布於不同的建築物間，因此感覺上人數比較稀疏，比較缺乏一群人共同研討的感覺。我所屬的 session 是在會議的第二天中午，這個 workshop 是由台灣學者所主持，可能是多個 sessions 同時進行，來聆聽的人數並不多，發問情況倒是不少。
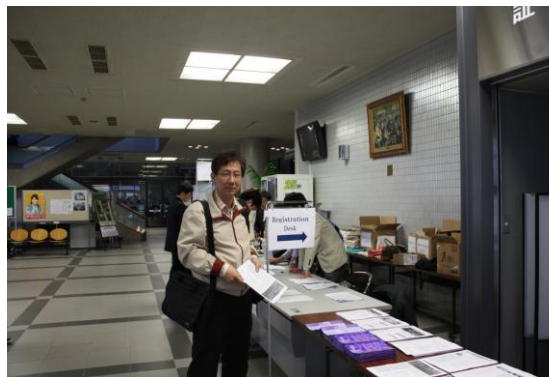
圖一　會場-福岡工業大學　　　　　　　　圖二　會場報到處

晚宴的地點不在福岡工業大學，而是在福岡市區的一個飯店內。晚宴內容採自助式方式以方便學者間的交流，參加的學者人數不少，坐滿了整個會場。晚宴中除了介紹工作人員、頒發論文獎及介紹下屆主辦單位地點之例行流程外，並穿插了日本傳統技藝表演。

圖三　晚宴會場　　　　　　　　　　　　　圖四　晚宴之表演

二、 與會心得

1. 會場的佈置不像國內辦研討會會花不少心思在會場佈置上，感覺比較沒有那麼個氣氛。
2. 會場至晚宴的飯店沒有提供交通車，較為不便。也許是因為日本人自認捷運交通工具十分發達，自行前往即可。
3. 國內方面出國留學的學生日漸減少，政府與學校單位鼓勵碩博士生出國參加會議是值得稱許的。

三、 考察參觀活動(無是項活動者省略)

自己參觀了福岡近郊的"日本孔廟"太宰府天滿宮。

四、 建議

1. 國內也常舉辦國際性研討會，可於議程中安排半日遊，讓外國學者增加認識台灣的機會，或於晚宴時安排有代表性的表演，如此對推展觀光也許有一些幫助。
2. 相關資訊的提供，包括會場地圖，搭車方式，飯店位置等，算是充足的，值得學習。

五、 攜回資料名稱及內容

Proceedings of the 2010 International Workshop on Intelligent Sensors and Smart Environments.

六、 其他

1. 日本的 JR 火車真準時。
2. 日本人民有禮貌，街道乾淨。想要發展服務業，提昇觀光產業的台灣，這些是值得學習的。不過，台灣的物價比日本便宜，這是相對有利點之一。
3. 感謝國科會工程處的補助。

論文被接受之證明文件**:**

We are pleased to inform you that your paper:

A 3D Model Retrieval System Based On The Cylindrical Projection Descriptor

has been accepted for presentation at ISSE-2010.

We would like to kindly remind you the following important issues:

Please follow EXACTLY the online Submission Guidelines

(http://isse2010.yuntech.edu.tw/), provided by the Conference Publishing

Services of the IEEE Computer Society and us, in the preparation of your

camera-ready copies. Please upload your camera-ready copies via the online

submission system (http://www.easychair.org/conferences/?conf=isse2010) by

July 23, 2010. In the submission system, you can use the item [Submit a new

version] to upload your camera-ready copies.

As a prerequisite of having your papers included in the proceedings,

conference registration is due by July 30, 2010.

Congratulations on this fine achievement! We are looking forward to seeing you

in Fukuoka in November 2010.

Sincerely,

Chien-Cheng Lee, PC chair

ISSE-2010

A 3D Model Retrieval System Based On The Cylindrical Projection Descriptor

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ABSTRACT

In recent years, the demand for a content-based 3D model retrieval system becomes an important issue. In this paper, the cylindrical projection descriptor (CPD) will be proposed for 3D model retrieval. To derive better retrieval results, the CPD will be combined with the radial distance descriptor (RDD). The experiments are conducted on the Princeton Shape Benchmark (PSB) database. Experiment results show that our proposed method is superior to others.

1. INTRODUCTION

Recent development in advanced techniques for modeling, digitizing and visualizing 3D models has made 3D models as plentiful as images and video. Therefore, it is necessary to design a 3D model retrieval system which enables the users to efficiently and effectively search interested 3D models. The primary challenge to a content-based 3D model retrieval system is how to extract the most representative features to discriminate the shapes of various 3D models [1].

Vranic et al. applied Fourier transform to the sphere with spherical harmonics to generate embedded multi-resolution 3D shape features [2]. To be rotation invariant, pose normalization must be conducted prior to feature extraction. Therefore, Funkhouser et al. proposed a modified rotation invariant shape descriptor based on the spherical harmonics in which no pose normalization is needed [3].

Some features to represent the 3D models are based on the histograms of geometric statistics. Ankerst et al. tried to search similar 3D models using shape histograms which characterize the area of intersections of a 3D model with a collection of concentric shells and sectors [4]. The MPEG-7 shape spectrum descriptor (SSD) [5] calculates the histogram of the curvatures of all points on the 3D surface. SSD represents the distribution of geometric characteristics and is robust to tessellation of 3D polygonal models. Osada et al. [6] proposed five features, A3, D1, D2, D3, and D4, to represent 3D models by the probability distributions of geometric properties computed from a set of randomly selected points located on the surface of the model. For instance, D2, the best feature among these five features, is the distribution of distances between two random points. However, these features are invariant to tessellation of 3D polygonal models. Thus, Shih et al. [7] proposed grid D2 (GD2) to improve D2. A 3D model is first decomposed into a voxel grid. The distribution of distances between any two randomly selected valid grids is measured to represent a 3D model.

The 3D models also can be described by its 2D silhouettes from different views. Users can find similar 3D models by 2D shape features. Super and Lu [8] exploit 2D silhouette contours for 3D object recognition. Curvature and contour scale space are extracted to represent each silhouette. Chen et al. [9] proposed the LightField descriptor (LFD) to represent 3D models. The LFD is computed from 10 silhouettes. Each silhouette is represented by a 2D binary image. The Zernike moments and Fourier descriptors are employed to describe each binary image. In fact, 2D silhouettes represented by binary images can not describe the altitude information of the 3D model from different views. Shih et al. [10] proposed the elevation descriptor (ED) to represent the altitude information of a 3D model from six views. However, LFD and ED represent only the exterior shape of 3D model without capturing the interior shape information.

Kuo and Cheng [11] proposed a 3D shape retrieval system based on the principal plane analysis. First, by projecting the 3D model onto its principal plane, a 3D model can be transformed into a 2D binary image. The feature vectors are then extracted from the binary shape image. However, using only one 2D binary image can not represent a complex 3D model well. Therefore, Shih et al. [12] proposed the principal plane descriptor (PPD) to describe a 3D model with three 2D binary images by projecting it on the principal, second and third planes. The proper feature vectors can be extracted from three binary images to do 3D model retrieval.

Novotni and Klein proposed a 3D shape retrieval method using 3D Zernike moments, which is naturally an extension of spherical harmonics based descriptors

[13]. Ricard et al. [14] presented a 3D shape descriptor, the 3D Angular Radial Transform (3D-ART) for 3D model retrieval. First, the 3D models are represented in spherical coordinates. Next, a Principal Components Analysis (PCA) is applied to align the 3D models along the z-axis. Then, the 3D extension of MPEG-7's ART [15] is applied to extract feature vectors.

Mademlis *et al.* [16] decomposed 3D models into meaningful parts and an attributed graph was constructed based on the connectivity of the parts. Then, the 3D Distance Field Descriptor (3D-DFD) was computed and associated to the corresponding graph nodes for partial and global 3D model retrieval.

Papadakis *et al.* [17] proposed two shape descriptors for 3D model retrieval. The 3D model was first aligned by continuous PCA (CPCA) or normal PCA (NPCA). In CPCA, the traditional one, the principal component is analyzed based on the covariance matrix computed from the coordinate vectors of the vertices, whereas in NPCA the covariance matrix is computed from the unit normal vectors of the mesh surfaces. The spherical harmonics was then applied on the filled 3D model to extract two feature vectors from the CPCA and NPCA aligned models separately. Vranic and Saupe proposed a modified PCA which used the corresponding triangle areas as weighting factors for covariance matrix computation [18]. The directions of 20 vertices on dodecahedron and the distances computed from the center point to the farthest intersections were used as features to index similar 3D models.

Zarpalas *et al.* [19] proposed a 3D model retrieval method using 240 (12×20) 2D gray-level projection images, which are obtained by projecting a 3D model onto the 240 planes rendered from the 12 vertices of 20 icosahedrons with different radii. Features were extracted from these gray-level images and combined to improve the performance. Another 3D model retrieval system used 20 depth images rendered from the 20 vertices of a dodecahedron [20]. The depth information of a pixel in each depth image was encoded as a 5-level character. Each row (depth line) in the depth image is then represented as a sequence of depth information. Dynamic programming was then used to compute the distance between two depth line descriptors.

In this paper, the cylindrical projection descriptor (CPD) will be proposed for 3D model retrieval. To derive better retrieval results, the CPD will be combined with the radial distance descriptor (RDD) [21]. The rest of the paper is organized as follows. In Section 2, the proposed 3D model retrieval method will be described. In Section 3, gives the experimental results to show the effectiveness of the proposed features. Finally, conclusions are given in Section 4.

2. THE PROPOSED 3D MODEL RETRIEVAL METHOD

In this study, two descriptors, including the radial distance descriptor (RDD) [21] and the cylindrical projection descriptor (CPD) are used for 3D model retrieval. Before extracting the feature vectors, the 3D model is aligned according to the principal plane [12].

2.1 Radial Distance Descriptor(RDD)

The main steps for computing the radial distance descriptor [21] are described as follows:

(1) 3D model is aligned by it's the principal plane [12]. The principal plane is defined as the symmetric plane on which the sum of distance of all points projected is minimal.

(2) The bounding cube is then decomposed into a voxel grid of size $100 \times 100 \times 100$ (see Fig. 1). A voxel located at coordinates (x, y, z) will be defined as an opaque voxel, notated as $Voxel(x, y, z) = 1$, if there is a mesh located within this voxel; otherwise, the voxel is defined as a transparent voxel, notated as $Voxel(x, y, z) = 0$. To normalize for translation and scale, the object's mass center, is moved to the point $(0, 0, 0)$ and the average distance from non-zero voxels to the mass center is scaled to 25.

(3) Six projection planes (see Fig. 1), which describe the radial distance from the 3D model surface to the mass center (see Fig. 2), are derived to represent a 3D model. Each projection plane is represented by a gray level image in which the gray value denotes the distance from an opaque voxel to the mass center (see Fig. 3). Let the six projection planes be notated as I_k, $k = 1, 2, \ldots, 6$. Then, the gray value of each pixel on these images is defined as follows:

$$I_1(x, z) = \max_{1 \le y \le 50}(\mathrm{R}(x, y, z)\mathrm{Voxel}(x, y, z)),$$
$$\text{for} -50 \le x, z \le 50,$$
$$I_2(x, y) = \max_{1 \le z \le 50}(\mathrm{R}(x, y, z)\mathrm{Voxel}(x, y, z)),$$
$$\text{for} -50 \le x, y \le 50,$$
$$I_3(y, z) = \max_{1 \le x \le 50}(\mathrm{R}(x, y, z)\mathrm{Voxel}(x, y, z)),$$
$$\text{for} -50 \le y, z \le 50,$$
$$I_4(x, z) = \max_{-50 \le y \le -1}(\mathrm{R}(x, y, z)\mathrm{Voxel}(x, y, z)),$$
$$\text{for} -50 \le x, z \le 50,$$
$$I_5(x, y) = \max_{-50 \le z \le -1}(\mathrm{R}(x, y, z)\mathrm{Voxel}(x, y, z)),$$
$$\text{for} -50 \le x, y \le 50,$$
$$I_6(y, z) = \max_{-50 \le x \le -1}(\mathrm{R}(x, y, z)\mathrm{Voxel}(x, y, z)),$$
$$\text{for} -50 \le y, z \le 50,$$

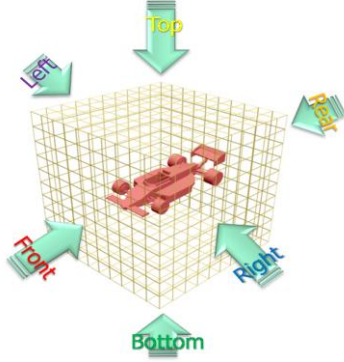where $\mathrm{R}(x, y, z) = \sqrt{x^2 + y^2 + z^2}$.

Fig. 1 The six views of 3D racing car model.
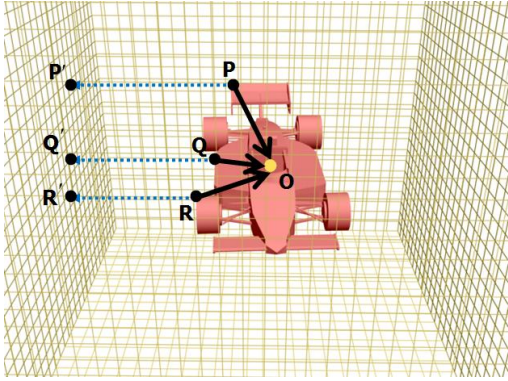

Fig. 2 The $\overline{PO}$, $\overline{QO}$, and $\overline{RO}$ represent the radial distance from the 3D model surface to the mass center O.
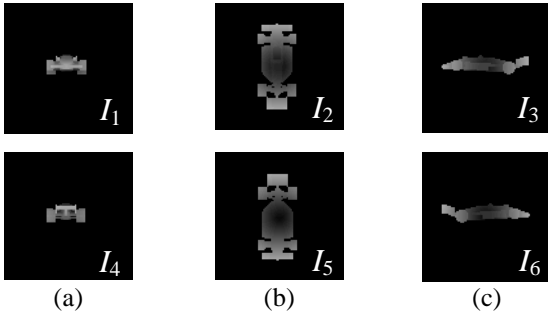

(a)   (b)   (c)

Fig. 3 3D racing car model and its six gray-level projection planes. (a) The front plane I_1 and the rear plane I_4. (b) The top plane I_2 and the bottom plane I_5. (c) The right plane I_3 and the left plane I_6.

(4) The MPEG7's angular radial transformation (ART) [15] is used to extract the feature vector from each projection plane. The ART descriptor consists of the magnitudes of all complex ART coefficients. In the MPEG-7 standard, the suggested ART descriptor consists of 35 coefficients, $\left| f_k^{\text{ART}}(n,m) \right|$, for $0 \leq n \leq 2$ and $0 \leq m \leq 11$, excluding $n = 0$ and $m = 0$. In summary, the radial distance descriptor (RDD) is defined as:

$$\mathbf{rdd} = [(\mathbf{rrd}_1)^T, (\mathbf{rrd}_2)^T, ..., (\mathbf{rrd}_6)^T]^T,$$

where $\mathbf{rdd}_k$, $1 \leq k \leq 6$, is the ART feature vector extracted from the k-th projection plane:

$$\begin{aligned}\mathbf{rdd}_k &= [\mathbf{rrd}_k(1), \mathbf{rrd}_k(2), ..., \mathbf{rrd}_k(35),]^T \\ &= [|f_k(0,1)|, ..., |f_k(0,11)|, |f_k(1,0)|, \\ &..., |f_k(1,11)|, |f_k(2,0)|, ..., |f_k(2,11)|]^T.\end{aligned}$$

2.2 The Cylindrical Projection Descriptor (CPD)

The main steps for computing the cylindrical projection descriptor (CPD) are described as follows:
(1) 3D model is aligned by it's the principal plane [12] as Sec 2.1.1.
(2) A cylindrical projection can unfold a portion of the surface of a sphere into a flat plane. (see Fig. 4).
As shown in Fig. 5, and 6, the three gray-level images F_1, F_2, F_3, can be obtained by mapping the $\overline{PO}$ value on the flat planes by three directions: **x**, **y**, and **z**.
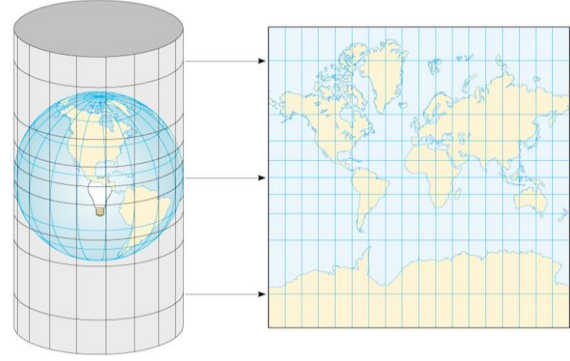
Fig. 4 The cylindrical projection.

(3) 2D-FFT (Fast Fourier Transform) is used to extract the feature vector from three 256×128 projection images (see Fig. 6). The FFT descriptor consists of the magnitudes of the first 32×32 FFT coefficients. In this paper, the FFT descriptor consists of 1024 coefficients, $\left| f_k^{\text{FFT}}(u,v) \right|$, for $0 \leq u \leq 31$ and $0 \leq v \leq 31$. In summary, the cylindrical projection descriptor (CPD) is defined as:

$$\mathbf{cpd} = [(\mathbf{cpd}_1)^T, (\mathbf{cpd}_2)^T, (\mathbf{cpd}_3)^T]^T$$

where $\mathbf{cpd}_k$, $1 \leq k \leq 3$, is the feature vector extracted from the k-th projection.

$$\begin{aligned}\mathbf{cpd}_k &= [\mathbf{cpd}_k(1), \mathbf{cpd}_k(2), ..., \mathbf{cpd}_k(1024),]^T \\ &= [|f_k(0,0)|, ..., |f_k(0,31)|, |f_k(1,0)|, \\ &..., |f_k(1,31)|, |f_k(31,0)|, ..., |f_k(31,31)|]^T.\end{aligned}$$

Fig. 5 The cylindrical projection descriptor. $\overline{PO}$ represent the distance from the 3D model surface to the mass.

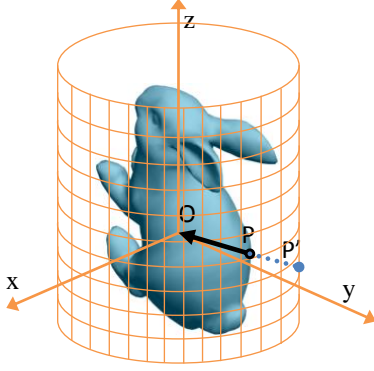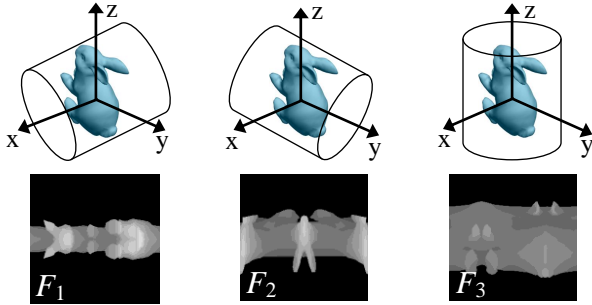Fig. 6 The three gray-level image F_1, F_2, and F_3, are obtained by the cylindrial projection.

2.3 Distance Computation

Let $\mathbf{rdd} = [(\mathbf{rdd}_1)^T, (\mathbf{rdd}_2)^T, ..., (\mathbf{rdd}_6)^T]^T$ and $\mathbf{rdd}^b = [(\mathbf{rdd}_1^b)^T, (\mathbf{rdd}_2^b)^T, ..., (\mathbf{rdd}_6^b)^T]^T$ denote the RDD of a query model and the b-th matching model in the database, respectively. The distance between the query model and the b-th matching model is defined as follows:

$$\mathrm{Dis}_{\mathrm{RDD}}^b = \frac{1}{N_{\mathrm{RDD}}} \sum_{k=1}^{6} \left\| \mathbf{rdd}_k - \mathbf{rdd}_k^b \right\|_1$$

$$= \frac{1}{N_{\mathrm{RDD}}} \sum_{k=1}^{6} \sum_{i=1}^{36} \left\| \mathrm{rdd}_k(i) - \mathrm{rdd}_k^b(i) \right\|$$

where $N_{\mathrm{RDD}} = 6 \times 36$. CPD is defined as:

Let $\mathbf{cpd} = [(\mathbf{cpd}_1)^T, (\mathbf{cpd}_2)^T, (\mathbf{cpd}_3)^T]^T$ and $\mathbf{cpd} = [(\mathbf{cpd}_1^b)^T, (\mathbf{cpd}_2^b)^T, (\mathbf{cpd}_3^b)^T]^T$ denote the CPD of a query model and the b-th matching model in the database, respectively. The distance between the query model and the b-th matching model is defined as follows:

$$\mathrm{Dis}_{\mathrm{CPD}}^b = \frac{1}{N_{\mathrm{CPD}}} \sum_{k=1}^{3} \left\| \mathbf{cpd}_k - \mathbf{cpd}_k^b \right\|_1$$

$$= \frac{1}{N_{\mathrm{CPD}}} \sum_{k=1}^{3} \sum_{i=1}^{1024} \left\| \mathrm{cpd}_k(i) - \mathrm{cpd}_k^b(i) \right\|$$

where $N_{\mathrm{CPD}} = 3 \times 1024$. Finall we use three kinds of similarity measure methods to combine RDD and CPD:

1) $\mathrm{Sim}_1^b = \dfrac{1}{\mathrm{Dis}_{\mathrm{RDD}}^b + \mathrm{Dis}_{\mathrm{CPD}}^b}$

2) Use the Borda Count Algorithm [34] to combine the RDD and CPD:

$$\mathrm{Sim}_2^b = \frac{1}{\mathrm{Rank}_{\mathrm{RDD}}^b + \mathrm{Rank}_{\mathrm{CPD}}^b}$$

where. $Rank_{\mathrm{RDD}}^b$ and $Rank_{\mathrm{CPD}}^b$ are the retrieval rank values of the b-th matching model for the RDD and CPD, respectively.

3. EXPERIMENTAL RESULTS

To demonstrate the effectiveness of the proposed method for different 3D models, some experiments have been conducted on the Princeton Shape Benchmark (PSB) database [23]. The PSB database contains 1814 models (161 classes) which are divided into 907 training models (90 classes) and 907 test models (92 classes). Note that in this database the number of models is different for each class. Since the number of models in each class is different in the PSB database, the *recall* value (Re_i^j) for the j-th query model in the i-th class is defined as follows:

$$Re_i^j = N_i^j / N_i,$$

where N_i^j denotes in the retrieval list the number of models labeled as class i and N_i is the total number of models in class i. The average recall values is defined as follows:

$$Re = \frac{1}{T_S} \sum_{i=1}^{92} \sum_{j=1}^{T_i} Re_i^j$$

where $T_s = T_1 + T_2 + \ldots + T_{92}$. The Discounted Cumulative Gain (DCG) [28], will also be employed to compare the performance of different approaches. DCG at the k-th rank is recursively defined as follows:

$$\mathrm{DCG}_k = \begin{cases} \mathrm{DCG}_{k-1} + \dfrac{L_k}{\log_2(k)}, & k \geq 2 \\ L_1, & k = 1 \end{cases},$$

where $L_k = 1$ if the k-th retrieval model and the query one belong to the same class; otherwise, $L_k = 0$. The overall DCG score for a query model q is defined as $\mathrm{DCG}_{k_{\max}}$, where k_{max} is the total number of models in the database. DCG is clear that if the top-ranked models and the query one are of the same class, $\mathrm{DCG}_{k_{\max}}$ will be larger than the retrieval result with similar models appearing in the bottom of the retrieval list.

In our experimental, each model in database is presented as a query one. Table 1 compares the

retrieval results of the proposed method with other descriptor. It also shows that the combination of RDD and CPD outperforms other descriptors in terms of the average recall value and DCG. The combination of RDD and CPD using the second similarly measure, Sim_2, has the best recall and DCG values. Moreover, we compare the retrieval performance of our proposed method with another state-of-the-art descriptors in Table 2. We can also see that the proposed method outperforms these descriptors in terms of DCG.

4. CONCLUSION

With the development of computer graphics and virtual realities, the demand for a content-based 3D retrieval system becomes urgent. In this study, two features, the radial distance descriptor (RDD) and the cylindrical projection distance (CPD) are combined for 3D model retrieval. The experiments have been conducted on the Princeton Shape Benchmark (PSB) database. Experiment results show that the proposed methods are superior to others.

5. ACKNOWLEDGEMENT

Table 1. Comparison of the proposed and other descriptors on the PSB database in terms of the *recall* value(%) and DCG(%). N_L denotes the number of retrieval models.

Method		Re $(N_L=T_i)$	Re $(N_L=4T_i)$	DCG
RDD		41.71	62.05	71.60
CPD		36.91	55.59	67.59
RDD+CPD	Sim_1	**43.53**	**62.27**	**72.05**
	Sim_2	42.75	61.75	71.15
ED[22]		35.48	56.03	67.04
AED [24]		38.61	60.29	70.29
DED[22]		36.19	55.87	66.92
CED[22]		37.32	57.80	68.04
PPD [12]		34.23	55.35	65.86
SH [3]		27.06	41.02	58.35
SSD [5]		15.87	26.64	48.07
GD2 [7]		28.30	47.61	60.91

Table 2. Comparison of the proposed method and other descriptors on the *PSB* database in terms of DCG(%). (Note that the approaches marked with * are implemented by Akgul et al. and originally appeared in [28])

Method		DCG	Method	DCG
RDD+CPD	Sim_1	**72.05**	DSR [27]*	66.50
EGI [25]		43.80	DBF [28]	65.90
CRSF [17]		66.80	DSR+DBF [28]	70.20
LF [9]		64.30	SWD [29]*	65.40
SH-GEDT [26]		58.40	SIL [27]*	59.70
DBI [27]*		66.30	3DHT [30]*	57.70
RISH [11]*		58.40	CAH [31]*	43.30
SHIST [13]*		54.50	REXT [32]*	60.10
			AVC [33]	60.20

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國科會補助計畫衍生研發成果推廣資料表

國科會補助計畫	計畫名稱: 整合三維頻率特徵及相關與非相關模型之自動選擇機制於3D模型檢索系統	
	計畫主持人: 石昭玲	
	計畫編號: 99-2221-E-216-045-	學門領域: 圖形辨識

無研發成果推廣資料

99 年度專題研究計畫研究成果彙整表

計畫主持人：石昭玲　　　計畫編號：99-2221-E-216-045-

計畫名稱：整合三維頻率特徵及相關與非相關模型之自動選擇機制於 3D 模型檢索系統

成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	3	3	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

	成果項目	量化	名稱或內容性質簡述
其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等,請以文字敘述填列。)	無		

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估 ■達成目標 □未達成目標（請說明，以 100 字為限） 　　　□實驗失敗 　　　□因故實驗中斷 　　　□其他原因 　說明：
2. 研究成果在學術期刊發表或申請專利等情形： 論文：□已發表 □未發表之文稿 ■撰寫中 □無 專利：□已獲得 □申請中 ■無 技轉：□已技轉 □洽談中 ■無 其他：（以 100 字為限）
3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限） 本計劃中我們提出了三種內部特徵，密度 3D-ART (Density 3D-ART Descriptor)、三維小曲率轉換(3D-Discrete Curvelet Transfom, 3D-DCT)和三維傅立葉轉換(3D-Discrete Fourier Transform, 3D-DFT)，並加以合併，檢索完結果發現合併後新的內部特徵超越了其他內部特徵 shell grid descriptor(SGD)、Grid D2(GD2)、Beta/distance histogram(BD)的正確率，未來我們將可把這些新的內部特徵與過去正確率較高之外部特徵如 ART-based elevation descriptor (AED)與 principal plane descriptor (PPD)等合併，去提升整個 3D 模型檢索系統之正確率。