**Object Recognition and Curvature Histograms**

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3D Recognition, Curvature Histograms, Archeology, Computer Science,

Sherd Identification, Bayesian Statistics, MYCIN

**Abstract:**

Using curvature histograms the problem of identifying partial 3 dimensional shapes was effectively reduced to a parameterized 1 dimensional problem. Thereby, the accurate identification of a set of partial 3D shapes to their original counterparts was possible by using this technique in combination with the development of an expert system that used Bayesian statistics.

**Introduction:**

One difficulty in the recognition of a 3 dimensional object is the vast number of ways that the object can be oriented. This large number makes the task of computer recognition quite laborious. For archeologists identifying and correctly categorizing diagnostic pieces is important evidence to look into past civilizations. By carefully studying the profile or curvature of these sherds, they may not only identify but reconstruct pots, separating pieces into useful categories. Creating an expert system by meeting its requirements with curvature histograms as method knowledgebase representation and using Bayesian statistics for the inference engine, can also do this. In this paper outlined are three steps demonstrating how identifying diagnostics accurately can be achieved. The first how to acquire an accurate curvature histogram that uniquely describes the profile; the second is how to acquire known curvature histograms for comparison; the third is how the proper application of statistical reasoning to the curvature histograms will identify diagnostics accurately.

**Material and Methods:**

Minolta VIVID 910 3D Digitizer

ActivePerl 5.10 Build 1001

Microsoft Office Excel 2003

Polygon Editing Tool Ver. 2.10 Beta

Sony Vaio VGN–FS630W (1.73 GHz Pentium M, 512 MB of RAM)

Test Shapes (Pot, Bowl, Paper Cup, Mug)

|  |
| --- |
| Fig.1 |
| Pot-oriented-0 |

|  |  |  |
| --- | --- | --- |
| Fig. 2 | | |
| Bowl-proto-e | Cup2-proto-e | Mug-proto-e |
| Bowl-prototype.obj | Cup2-prototype.obj | Mug-prototype.obj |
|  | Pot-proto-e |  |
|  | Pot-prototype.obj |  |

To begin the needed digital 3D files were created by carefully scanning each shape using Minolta VIVID 910 3D Digitizer approximately 45° above the horizontal. Also a mirror and a lens cap were used to separate and elevate the object from the scanning surface (fig.1). Typically an average of 6 scans or elements was used in the creation each digital 3D object file. These elements were the then put together using Polygon Editing Tool’s manual registration function. Using 6 or 7 points to align the individual elements kept error at a minimum. All these elements were merged to create a single 3D object or element. Then this merged element was smoothed using Polygon Editing Tool’s ‘smooth elements’ function set to its default settings. This single merged element was then exported in Wavefront Technologies’ OBJ format, so that individual points in the merged elements point cloud’s Cartesian coordinates could be readily extracted. To create the curvature histograms correctly the elements were rotated until the corresponding shapes could be easily identified as a 2D picture in the x-y plane (fig. 2). From the projection of each of these the corresponding histograms became the basis for the knowledge base. The partial pieces left over from the creation process were used as the unknown ‘broken’ objects (fig. 3).

|  |  |  |
| --- | --- | --- |
| Fig. 3 | | |
| piece1e | piece2e | piece3e |
| piece1.obj | piece2.obj | piece3.obj |
| piece4e | piece5e | piece6e |
| piece4.obj | piece5.obj | piece6.obj |

The curvature histograms were created by projecting the each object onto the x-y plane and then analyzing its profile repeatedly. The final histogram was an aggregate of the individual analyst of profiles as the object was rotated in the x-z and y-z planes about the object’s centroid. The centroid was chosen to minimize the effect of the initial orientation of each piece during the analysis. Additionally the units of the projected plane were determined automatically by measuring the distance from the object’s centroid to its farthest point using eq.1.

C + (2\*Rs\*Rmax(x,y,z)) (eq.1)

Where Rs is a user defined constant that influences the resolution, and Rmax(x,y,z) is the maximum distance from the centroid to the object’s edge. The constant C was used to ensure that the object lies within the plane. The value 10 was chosen for C, however any positive number could be used. Therefore truncating the results from eq.1 gives the square units of the plane the rotating object is projected onto. Finally, the curvature histogram was created by taking 3 adjacent points along the edge of the projected object.

|  |
| --- |
| Fig.4 |
|  |

The inference engine used to compare these histograms was based off of the MYCIN expert system

CF[h,e] = MB[h,e] – MD[h,e] (p.234, Rich) (eq.2)

Where CF is the confidence factor, MB is the measured belief in hypothesis h giving the evidence e, MD is the measured disbelief in hypothesis h giving the evidence e. This was modified to:

CFi[hi,e1,e2] = MB[hi,e1] + WD\*MD[hi,e2] (eq.3)

Where e1 is the evidence supporting hypothesis hi, e2 is the evidence refuting hypothesis hi, and WD is a constant that weights the measured disbelief into the confidence factor. The sign was changed to reflect measured disbeliefs can be negative signifying a very poor fit which was often the case. Each ‘unknown’ piece was compared to each histogram in the knowledgebase resulting in a set of values using eq. 3. To compare each ‘unknown’ piece its parameterized curvature histogram was searched linearly to find a value that matched the initial value of the knowledgebase’s parameterized curvature histogram that was actively being compared. Once a match was found the correlation between them was found, the maximum value the measured belief and the minimum value the measured disbelief manufacturing the values of the set that the repeated use of eq. 3 gives. The largest of this set of values represents with how much confidence which object out of the knowledgebase did the ‘unknown’ piece belong to.

**Results:**

|  |  |
| --- | --- |
| Program settings | Description |
| Run Mode: 0 0 0 1 | Only, compare created files. |
| Offset Switch = 0 | Searches for offset for comparisons |
| Curvature Ceiling = 1 | limits offset search to reasonable numbers |
| Curvature Bias = 1 | Weights curvature, deemphasizes lines |
| Tolerance = 0 | Percent difference required for comparison |
| Remove negative fits = 0 | Removes negative fits |
| Worst Run Weighting = 0.5 | weight calculated into confidence |
| Best fit averaging = 5.00% | Averages the top 5.00% fits. |
| Rotation resolution = 2.5° | Angle of rotation during histogram creation |

Start time: 2008:3:11:19:35:50 Results8.txt

piece1.hst Bowl-prototype.prt 0.627820134228188

piece1.hst Cup2-prototype.prt 0.316072483221478

piece1.hst Mug-prototype.prt 0.698988590604025

piece1.hst Pot-prototype.prt 0.806552348993288

piece2.hst Bowl-prototype.prt 0.622102150537636

piece2.hst Cup2-prototype.prt 0.316083333333335

piece2.hst Mug-prototype.prt 0.69260483870968

piece2.hst Pot-prototype.prt 0.80059005376344

piece3.hst Bowl-prototype.prt 0.826423444976076

piece3.hst Cup2-prototype.prt 0.248662679425838

piece3.hst Mug-prototype.prt 0.925679425837318

piece3.hst Pot-prototype.prt 0.866165071770334

piece4.hst Bowl-prototype.prt 0.650833333333333

piece4.hst Cup2-prototype.prt 0.301107526881722

piece4.hst Mug-prototype.prt 0.673161290322581

piece4.hst Pot-prototype.prt 0.667172043010752

piece5.hst Bowl-prototype.prt 0.553184426229507

piece5.hst Cup2-prototype.prt 0.769930327868851

piece5.hst Mug-prototype.prt 0.538463114754098

piece5.hst Pot-prototype.prt 0.577487704918033

piece6.hst Bowl-prototype.prt 0.795504225352114

piece6.hst Cup2-prototype.prt 0.109060563380285

piece6.hst Mug-prototype.prt 0.773385915492959

piece6.hst Pot-prototype.prt 0.682138028169015

piece1.hst belongs to Pot-prototype.prt confidence: 0.807

piece2.hst belongs to Pot-prototype.prt confidence: 0.801

piece3.hst belongs to Mug-prototype.prt confidence: 0.926

piece4.hst belongs to Mug-prototype.prt confidence: 0.673

piece5.hst belongs to Cup2-prototype.prt confidence: 0.770

piece6.hst belongs to Bowl-prototype.prt confidence: 0.796

All six pieces were correctly identified.

**Discussion:**

According to the program log files these 10 files were processed in approximately 47 min. The parameters such as the offset, weighting, and tolerance settings change run times significantly ranging from a few minutes to a few hours. I however found the above settings to be the most accurate. I am confident this time could be reduced by writing a more efficient algorithm for computation and by translating the program to C or Java for so that resources could be more effectively managed. You may notice that piece 4 has a confidence rating of 0.673. This was expected, as this piece of the mug was missing the identifying feature or handle. This also made it the most difficult for my program to identify correctly. One could argue that a mug is just a cup with a handle so without the handle it is just a cup. So naturally I was very pleased with this result and did not expect my program to match this piece with a high level of confidence. Similarly incorporated into the confidence is a penalty if comparisons end up fitting poorly receiving negative correlations (eq.3), from which piece 5 may have suffered.

**Conclusions:**

I set out to outline three steps demonstrating how identifying diagnostics accurately can be achieved. I have shown that the acquisition of an accurate representation of a curvature histogram that describes a profile that is unique can be accomplished with reasonable amount of certainty; that was the first step. The second was the acquisition of known data to for comparison. Using the Minolta 3D scanner I was able to create a digital representation of 3D objects to be compared. However there are no 3D archeological prototypes in existence (p.4, Kampel), but because my program compares profiles there is no need for an actual 3D archeological pot to use as prototypes. One may scan drawings from catalogs and build prototype histograms from that data. Then one can proceed to scanning actual sherds three dimensionally and perform fits, and thus accomplishing the second step. The third step is the proper application of statistical reasoning to identify diagnostics accurately. I was able to match all 6 pieces without errors. My program uses a simple confidence factor reasoning engine similar to that of the MYCIN system, so it is a pure Bayesian system. One of drawbacks of systems of this type is that all searches must be exhaustive. My 10 files had to be compared in 24 different combinations before there could be any results, this may be fine for small samples but very time consuming for large samples. I believe that these results by be improved with the addition of a more sophisticated reasoning engine. Dempster-Shafer Theory provides a framework for such an engine with the interval.

[Belief, Plausibility] (p.242, Rich)

The belief would be supplied by correlation data similar to those in my results, and the plausibility would be assigned by an expert in the field. The correlation data would be based on fitting identifying features rather than entire shapes. For example the reasoning engine could be described in this fashion; because Feature A and Feature B have X and Y beliefs respectively, P is concluded with C confidence. I believe that Dempster-Shafer Theory provides a superior technique to that of MYCIN in this regard, and would better accomplish the third and final step in identifying potter sherds.

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