

# Computing and Rendering Point Set Surfaces

Marc Alexa, et.al.  
IEEE TVCG 9(1), Jan 2003

Presented by Matthew Bolitho

24 October 2005

# Manifold Surfaces

## Definition

“A manifold is a topological space that is locally Euclidean” –  
Mathworld

# Manifold Surfaces

## Definition

“A manifold is a topological space that is locally Euclidean” –  
Mathworld

- Around every point there is a local neighbourhood that is topologically the same as an open unit ball.

# Manifold Surfaces

## Definition

“A manifold is a topological space that is locally Euclidean” –  
Mathworld

- Around every point there is a local neighbourhood that is topologically the same as an open unit ball.
- We can create local parameterised neighbourhoods that cover the entire surface.

# Approach

- A point set defines an implicit surface.

# Approach

- A point set defines an implicit surface.
- Define a map  $\pi$  that projects a point near the surface onto the surface.

# Approach

- A point set defines an implicit surface.
- Define a map  $\pi$  that projects a point near the surface onto the surface.
- The surface is formed from all points s.t.  $\pi(p) = p$ .

# Approach

- A point set defines an implicit surface.
- Define a map  $\pi$  that projects a point near the surface onto the surface.
- The surface is formed from all points s.t.  $\pi(p) = p$ .
- The map  $\pi$  is created from Moving Least Squares.



# Moving Least Squares

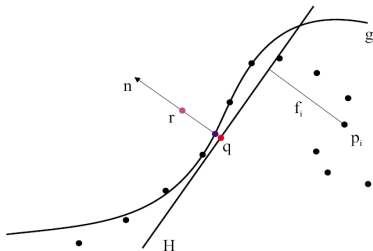


Figure from Alexa03

- A reference domain  $H$  is formed from the neighbourhood around  $r$ .

# Moving Least Squares

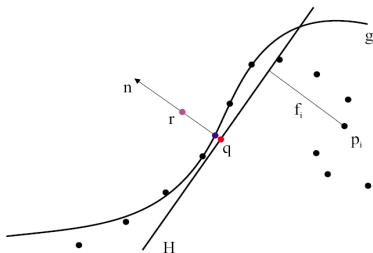


Figure from Alexa03

- Point  $q$  is the projection of  $r$  onto the plane  $H$ .

# Moving Least Squares

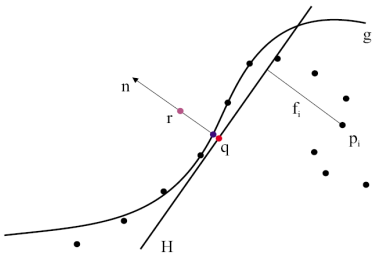


Figure from Alexa03

- A polynomial  $g$  approximates the height function  $f$ .

# Moving Least Squares

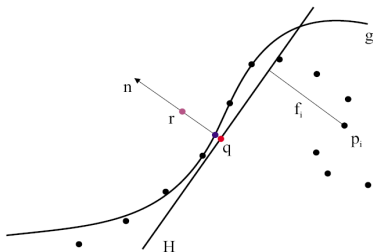


Figure from Alexa03

- $f_i = \text{dist}(p_i, H)$  weighted by  $\text{dist}(p_i, q)$

# Moving Least Squares

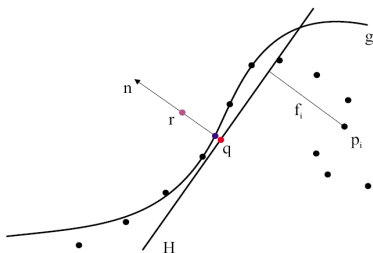


Figure from Alexa03

- The map  $\pi(p)$  projects  $p$  onto  $g$

# Shape Representation

## Claim

Points can be used as a complete representation of shape (i.e. no polygonal mesh representation)

# Shape Representation

## Claim

Points can be used as a complete representation of shape (i.e. no polygonal mesh representation)

- Provided the sampling is sufficiently dense, all features captured

# Shape Representation

## Claim

Points can be used as a complete representation of shape (i.e. no polygonal mesh representation)

- Provided the sampling is sufficiently dense, all features captured
- Given a collection of points, one can define a manifold



# Shape Representation

## Claim

Points can be used as a complete representation of shape (i.e. no polygonal mesh representation)

- Provided the sampling is sufficiently dense, all features captured
- Given a collection of points, one can define a manifold
- In detailed models, triangles often project to  $\leq 1$  pixel – render as points anyway

# Shape Representation

## Claim

Points can be used as a complete representation of shape (i.e. no polygonal mesh representation)

- Provided the sampling is sufficiently dense, all features captured
- Given a collection of points, one can define a manifold
- In detailed models, triangles often project to  $\leq 1$  pixel – render as points anyway

## Question

Is this resonable?

# Resampling

- A point set may be noisy and over or under sampled

# Resampling

- A point set may be noisy and over or under sampled
- Once a projection map  $\pi$  is known everywhere:

# Resampling

- A point set may be noisy and over or under sampled
- Once a projection map  $\pi$  is known everywhere:
  - Noise can be reduced by mapping all points into the smooth manifold surface

# Resampling

- A point set may be noisy and over or under sampled
- Once a projection map  $\pi$  is known everywhere:
  - Noise can be reduced by mapping all points into the smooth manifold surface
  - Points can be removed to decimate the point set (remove the point that contributes least to  $g$ )

# Resampling

- A point set may be noisy and over or under sampled
- Once a projection map  $\pi$  is known everywhere:
  - Noise can be reduced by mapping all points into the smooth manifold surface
  - Points can be removed to decimate the point set (remove the point that contributes least to  $g$ )
  - Points can be added by placing them near the surface, then mapping them onto the surface with  $\pi$

# Weighting Function

- When computing the polynomial  $g$ , each point is weighted as:  
$$\theta(d) = e^{\frac{-d^2}{h^2}}$$

Where  $d = \text{dist}(p_i, q)$  and  $h$  is the variance.



# Weighting Function

- When computing the polynomial  $g$ , each point is weighted as:  
$$\theta(d) = e^{\frac{-d^2}{h^2}}$$

Where  $d = \text{dist}(p_i, q)$  and  $h$  is the variance.

- Note that  $d$  is defined from  $q$  not  $r$ .

# Weighting Function

- When computing the polynomial  $g$ , each point is weighted as:  
$$\theta(d) = e^{\frac{-d^2}{h^2}}$$

Where  $d = \text{dist}(p_i, q)$  and  $h$  is the variance.

- Note that  $d$  is defined from  $q$  not  $r$ .
- If  $h$  is small, then the neighbourhood of points in  $H$  is also small, and  $g$  captures more detail.

# Weighting Function Example



Figure from Alexa03

# Advantages

- Space requirement proportional to  $h$ , not  $|P|$ .

# Advantages

- Space requirement proportional to  $h$ , not  $|P|$ .
- Generates a  $C^\infty$  manifold.

# Advantages

- Space requirement proportional to  $h$ , not  $|P|$ .
- Generates a  $C^\infty$  manifold.
- Nice application of differential geometry.

# Advantages

- Space requirement proportional to  $h$ , not  $|P|$ .
- Generates a  $C^\infty$  manifold.
- Nice application of differential geometry.
- $h$  doesn't have to be a global paramter

# Disadvantages

- Hard to assess the time requirements: 1500-3500 points per second on a “standard Pentium PC”

But 10-30 seconds for the 36,000 point bunny seems slow.