

A Concise and Provably Informative Multi-Scale Signature Based on Heat Diffusion

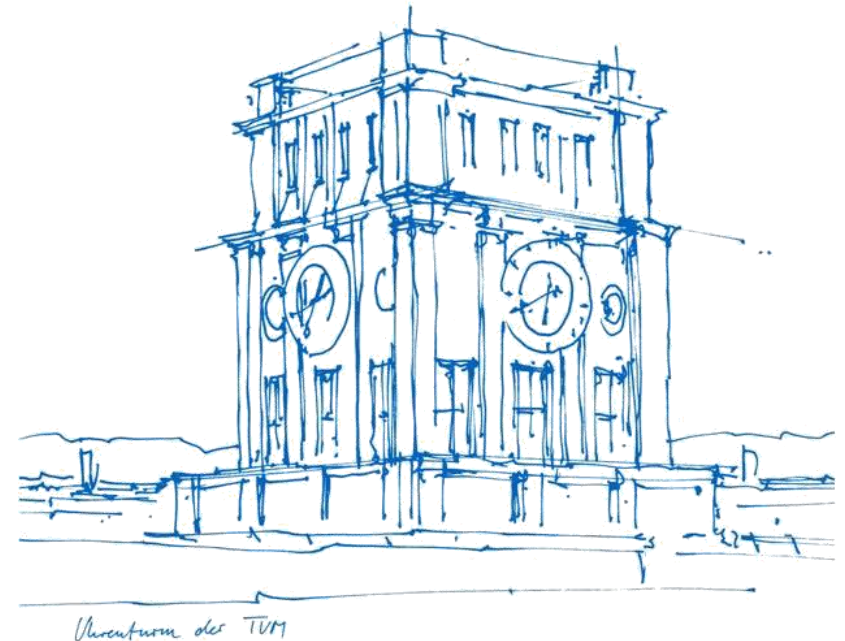
Jian Sun, Maks Ovsjanikov, Leonidas Guibas (2009)

Presented by: Julia Fokuhl

Technische Universität München

Image Segmentation and Shape Analysis

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Motivation

Characterise shapes

Gain information about the geometry

Identify features

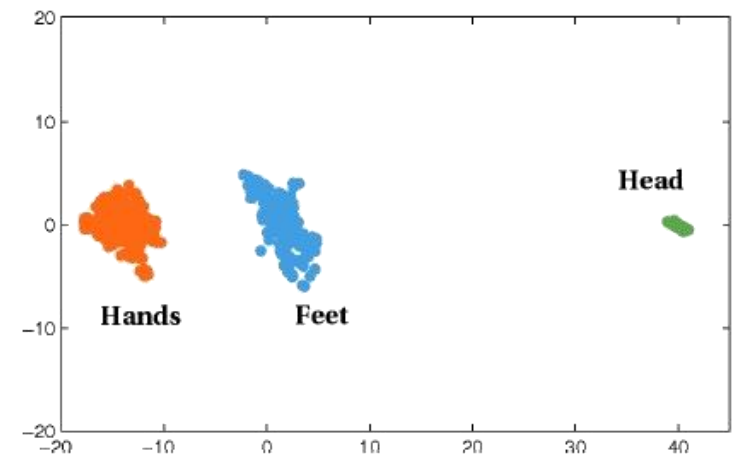


Motivation - Applications

Shape Comparison/ Matching shapes

Detect repeated structures
(across one or more shapes)

Classification



Heat Kernel Signature (HKS)

Point signature based on heat diffusion

Preserves information about intrinsic geometry

Properties:

- Efficient calculation
- Concise
- Multi-scale
- Stable
- Invariant under isometric deformations



Heat Diffusion

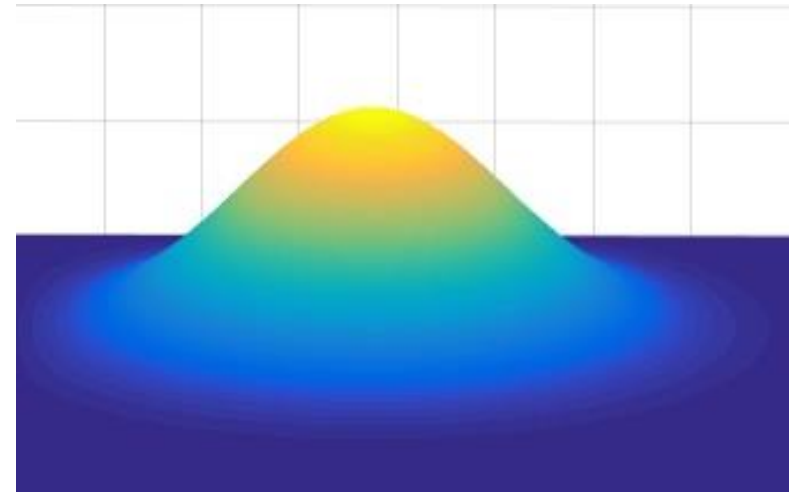
on a compact Riemannian manifold M :

$$\Delta u(x, t) = - \frac{\partial u(x, t)}{\partial t}$$

with

Δ : Laplace-Beltrami-Operator

$u(x, t)$: heat distribution at point x and time t



If M has boundaries, the Dirichlet boundary condition has to be fulfilled:

$u(x, t) = 0$ for all $x \in \partial M$ and all t

Heat Diffusion

$$\Delta u(x, t) = - \frac{\partial u(x, t)}{\partial t}$$

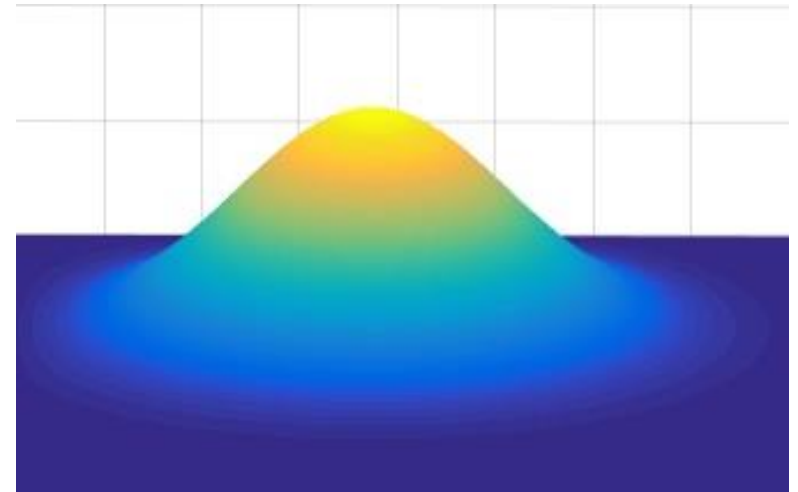
Initial heat distribution $f : M \rightarrow \mathbb{R}$

Heat distribution after time t

→ Heat Operator: $H_t(f)$

Relation for the operators: $H_t = e^{-t\Delta}$

thus both operators H_t and Δ share the same eigenfunctions



Heat Kernel

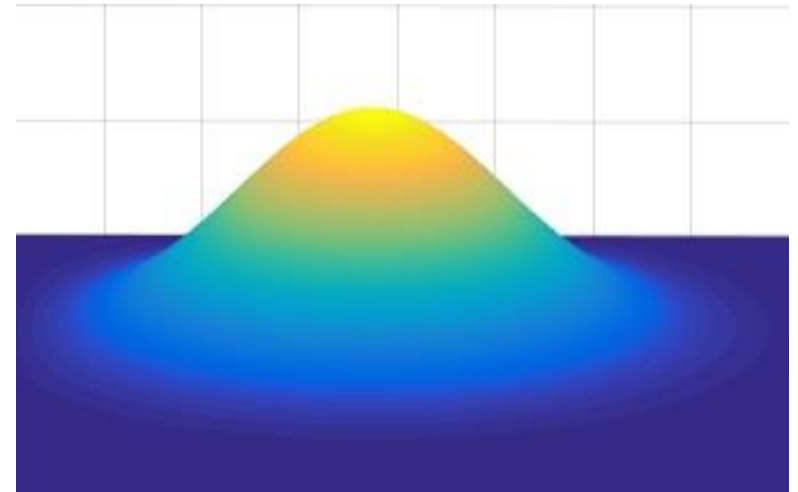
$$\Delta u(x, t) = - \frac{\partial u(x, t)}{\partial t}$$

$$H_t f(x) = \int_M k_t(x, y) f(y) dy$$

dy : volume form at $y \in M$

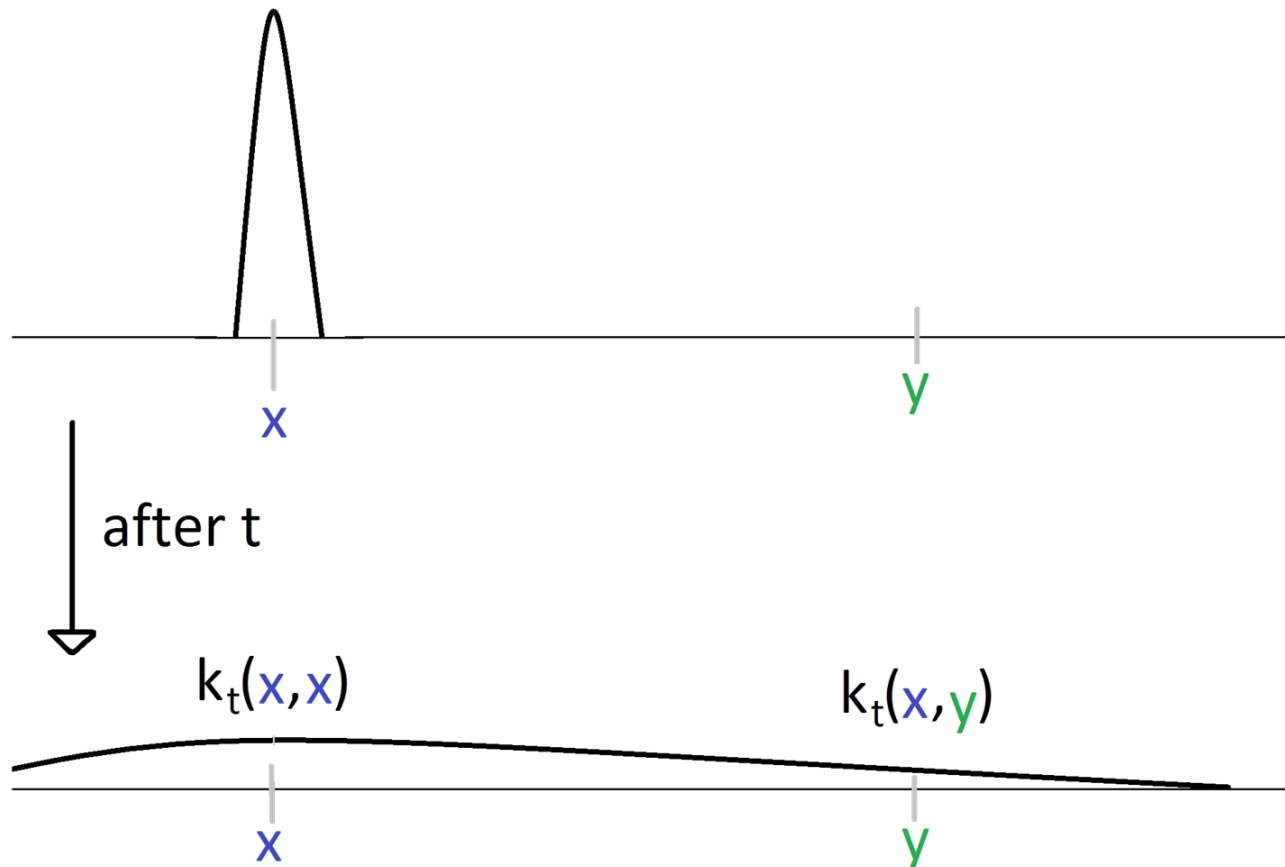
$k_t(x, y)$: heat kernel (amount of heat transferred from x to y in time t given a unit heat source at x)

$k_t(x, \cdot) = H_t(\delta_x)$ with δ_x : Dirac-Delta



Heat Kernel

amount of heat transferred from x to y in time t given a unit heat source at x



Heat Kernel

can be represented in the Laplace-Beltrami eigenbasis

Eigendecomposition:

$$k_t(x, y) = \sum_{i=0}^{\infty} e^{-\lambda_i t} \phi_i(x) \phi_i(y)$$

$\phi_i(x)$: i^{th} eigenfunction of the Laplace-Beltrami-Operator

λ_i : i^{th} eigenvalue of the Laplace-Beltrami-Operator

Repetition: Intrinsic Isometry

Mapping $\Phi: M \rightarrow N$ between two shapes M, N is an isometry, if the geodesic distances are preserved

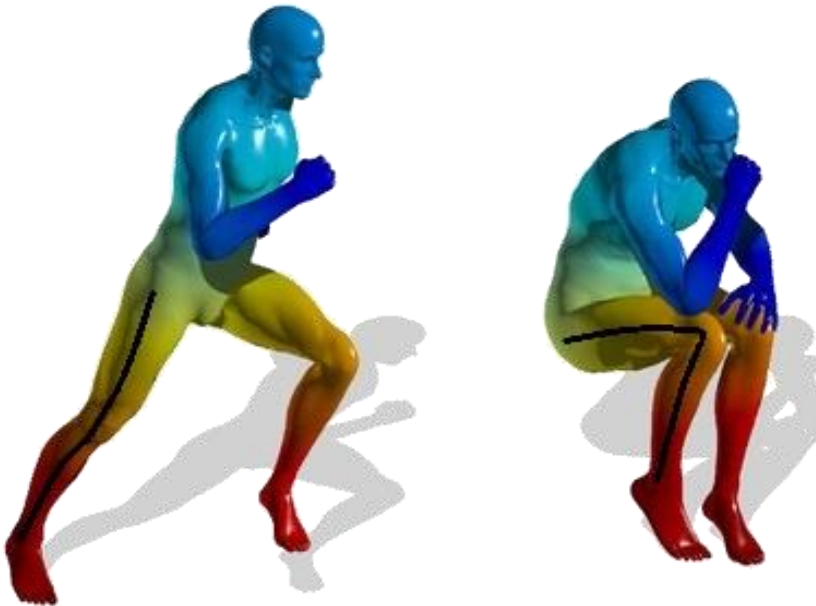


Image adapted from:
Shtern, A.; Kimmel, R. Matching the LBO
Eigenspace of Non-Rigid Shapes via High
Order Statistics. *Axioms* **2014**, 3, 300-319.

Heat Kernel

is intrinsic \rightarrow is an isometric invariant

If $\Phi : M \rightarrow N$ is an isometry between Riemannian manifolds M and N , then $k_t^M(x, y) = k_t^N(\Phi(x), \Phi(y))$ for any $x, y \in M$ and $t > 0$

is informative \rightarrow fully characterises shapes up to isometry

Let $\Phi: M \rightarrow N$ be surjective map between Riemannian manifolds M and N

If $k_t^M(x, y) = k_t^N(\Phi(x), \Phi(y))$ for any $x, y \in M$ and $t > 0$, then Φ is an isometry

Heat Kernel

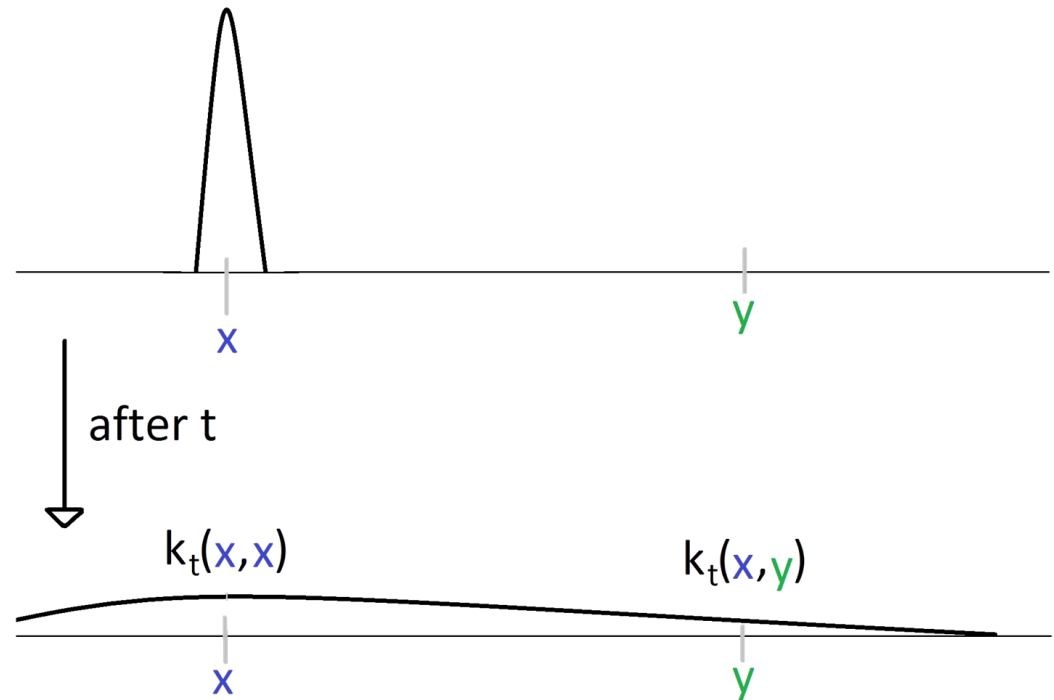
Family of functions $\{k_t(x, \cdot)\}_{t>0}$

High complexity:
defined on $\mathbb{R}^+ \times M$

Redundant information
→ Heat Kernel Signature

$$HKS(x, t) = k_t(x, x)$$

for a point x on the manifold M : $HKS(x): \mathbb{R}^+ \rightarrow \mathbb{R}$,



Heat Kernel Signature

$$HKS(x, t) = k_t(x, x)$$

Dropping spatial domain

$\{ k_t(x, x) \}_{t>0}$ is almost as informative as $\{ k_t(x, \cdot) \}_{t>0}$

HKS at different points are defined on a common temporal domain

→ Easily commensurable

Properties:

- ✓ Efficient calculation
- ✓ Concise
- Multi-scale
- Stable
- Invariant under isometric deformations

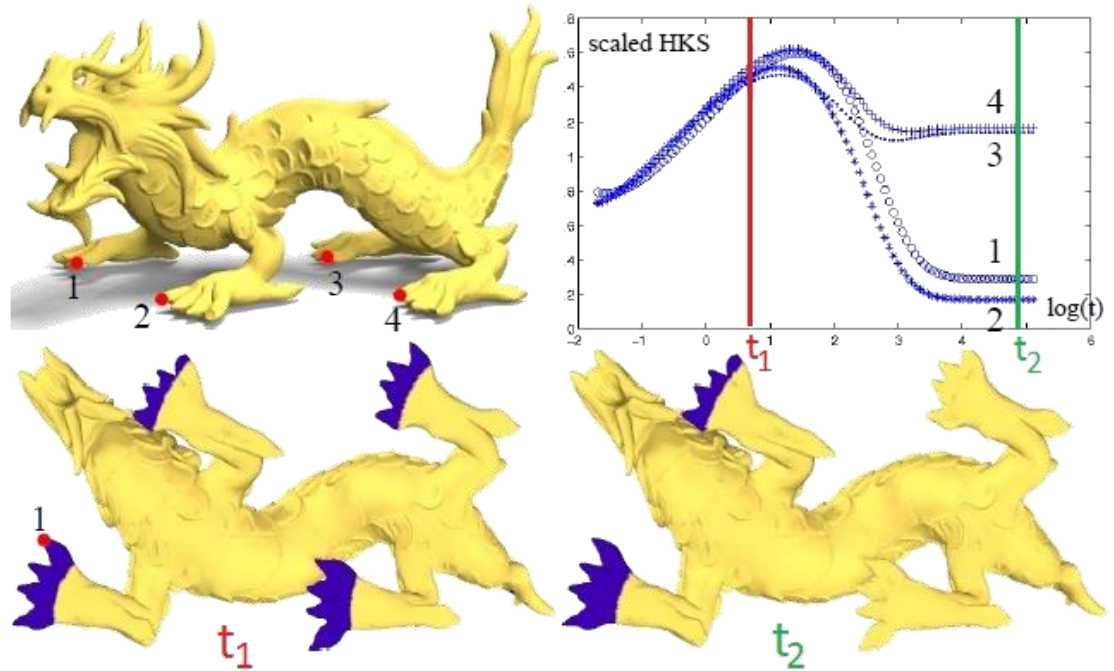
Time as scaling parameter

Dissipation of heat from a point x
 Heat diffuses progressively to larger neighbourhoods

Highly local features/
 Small Neighbourhood
 – observed at short times

Big features/ Global Structure
 – observed after long times

→ Time as scaling parameter
 → Multi-scale Signature



Multiscale

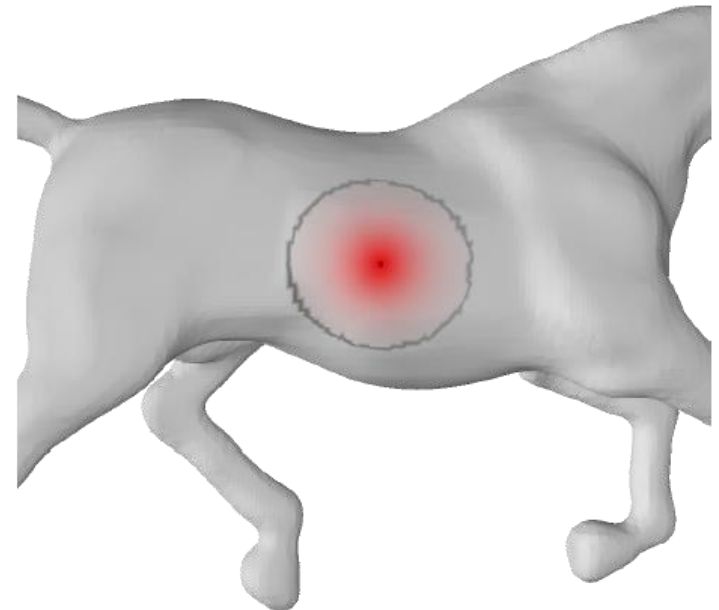
Subset $D \subseteq M$ (D: grey circle on horse)

$k_t^D(x, y)$ is a good approximation of $k_t(x, y)$ in case that

- D is arbitrary small as long as t is small

$$\lim_{t \rightarrow 0} k_t^D(x, y) = k_t(x, y)$$

- t is arbitrary large as long as D is big



Multiscale

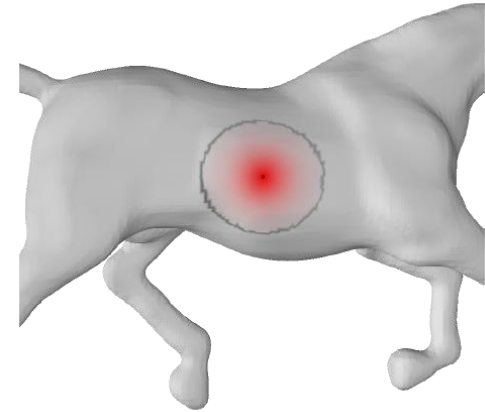
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HKS in discrete settings

Underlying manifold unknown

Approximation by mesh with n vertices

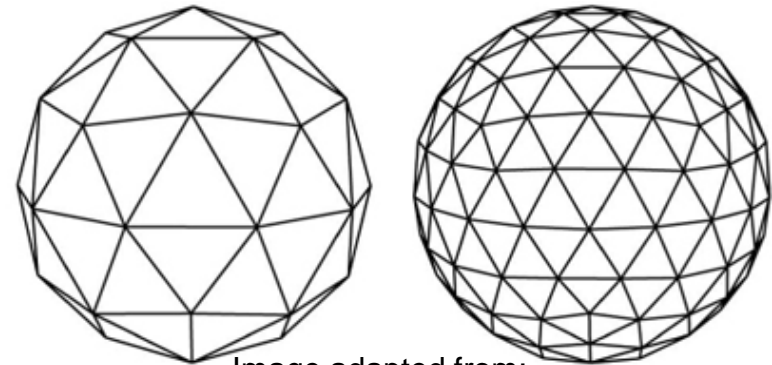


Image adapted from:

<http://hessan.annahid.com/images/gdd/geosphere.gif>

Estimation of the Laplace-Beltrami Operator: Mesh Laplace Operator L^1

$$L = A^{-1}W$$

L : sparse matrix of size $n \times n$

A : positive diagonal matrix

$A(i, i)$ represents an area associated with vertex i

W : symmetric semi-definite matrix

[1]: Belkin M., Sun J., Wang Y.: Discrete Laplace operator on meshed surfaces. In *Proceedings of SOGC (2008)*, pp.278-287

HKS in discrete settings

Heat Equation on the mesh:

$$Lu_t = -\frac{\partial u_t}{\partial t}$$

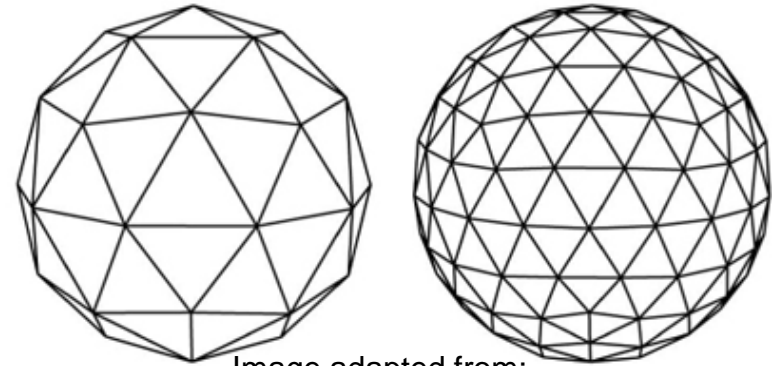


Image adapted from:
<http://hessan.annahid.com/images/gdd/geosphere.gif>

Reminder for continuous case:

$$\Delta u(x, t) = -\frac{\partial u(x, t)}{\partial t}$$

$u_t(x)$: time-dependent function defined on a vertex x at time t

HKS in discrete settings

$$u_t = e^{-tL} f$$

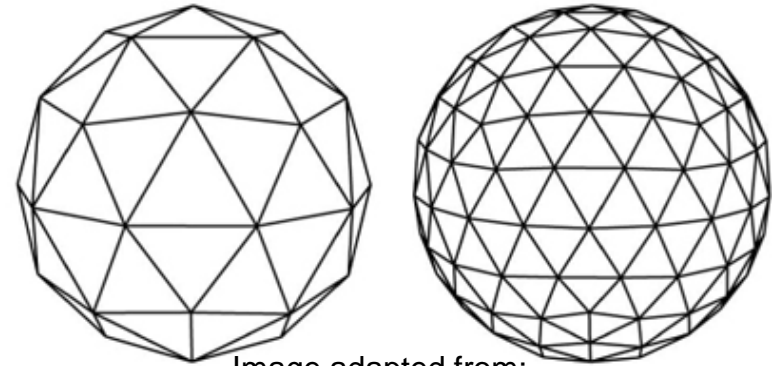


Image adapted from:

<http://hessan.annahid.com/images/gdd/geosphere.gif>

$$u_t(x) = \sum_y k_t(x, y) f(y) A(y)$$

$$k_t(x, y) = \sum_{i=0}^n e^{-\lambda_i t} \phi_i(x) \phi_i(y)$$

Matching Points

HKS encodes information about the neighbourhood of a point

Matching \rightarrow Compare HKS of two points in a specific interval $[t_1, t_2]$

$$\left(\int_{t_1}^{t_2} |k_t(x, x) - k_t(x', x')|^2 dt \right)^{1/2}$$

Successful match if expression is approximately 0

Matching Points

Heuristic adaptations:

$|k_t(x, x) - k_t(x', x')|$ decreases with increasing t
→ At small scales differences seem larger

Reminder: $k_t(x, x) = \sum_i e^{-\lambda_i t} \phi_i^2(x)$

Use normalisation:

Scale with $\int_M k_t(x, x) dx$

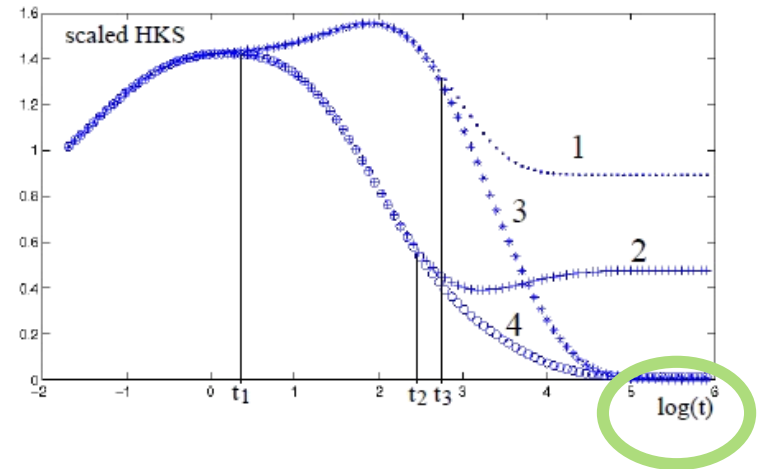
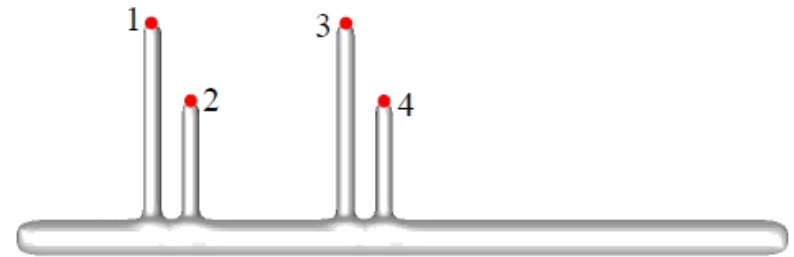
Matching Points

Heuristic adaptations:

$k_t(x, x)$ varies strongly between small times
 slower variation for larges times

Intuitive explanation:
 HKS changes more rapidly at small scales,
 large neighbourhoods are rather stable

→ Scale temporal domain logarithmically



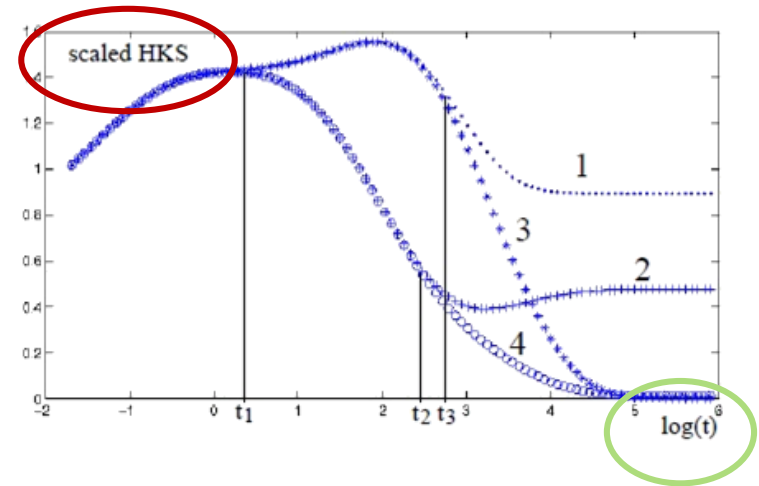
Matching Points

Heuristic adaptations:

→ Scale with $\int_M k_t(x, x) dx$ (normalisation)

→ Scale temporal domain logarithmically

Difference between two Heat Kernel Signatures:



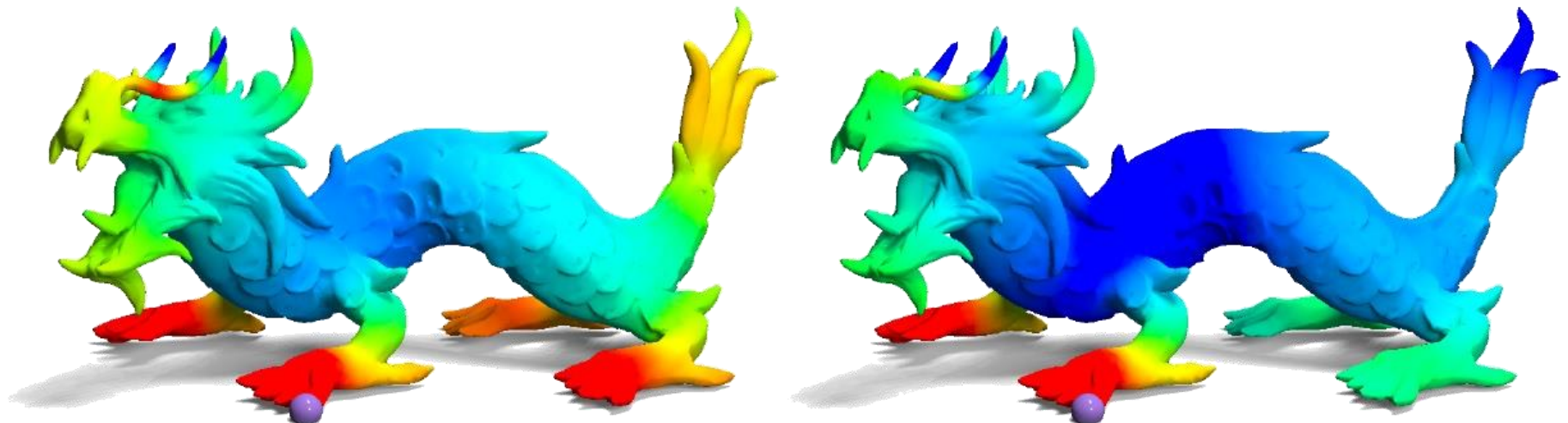
$$d_{[t_1, t_2]}(x, x') = \left(\int_{t_1}^{t_2} \left(\frac{|k_t(x, x) - k_t(x', x')|}{\int_M k_t(x, x) dx} \right)^2 d(\log t) \right)^{1/2}$$

Matching Points

$$d_{[t_1, t_2]}(x, x') = \left(\int_{t_1}^{t_2} \left(\frac{|k_t(x, x) - k_t(x', x')|}{\int_M k_t(x, x) dx} \right)^2 d(\log t) \right)^{1/2}$$

Distance function between HKS of purple point to all other points:

Red → difference ≈ 0 **Blue** → highest difference to purple point



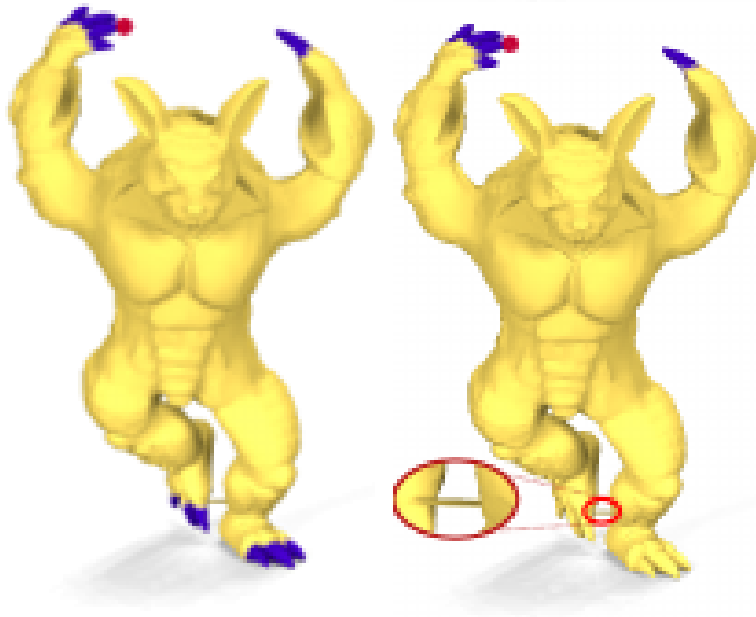
Small t

Larger t

Special Benefits of the HKS

Resilience to Noise:

Small tunnel between feet models noise
Method still works reliably



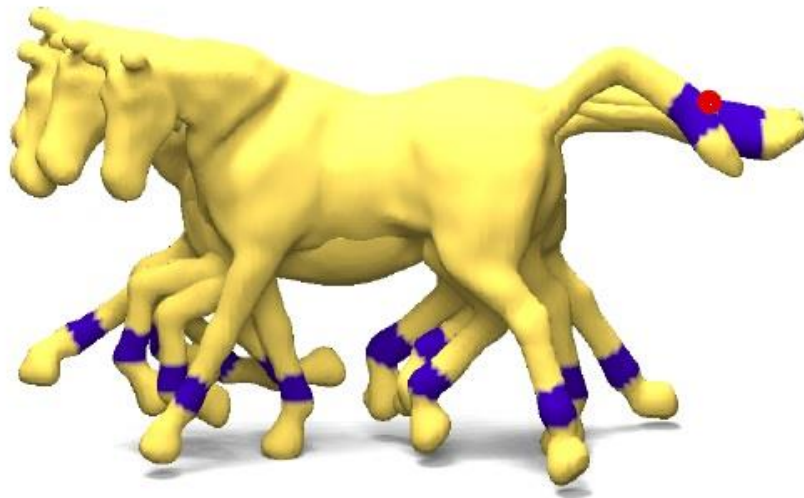
Properties:

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Special Benefits of the HKS

Comparing features across several shapes:
Possible due to invariance under isometric deformations

4 independent datasets (poses) of a horse
Marked: Signatures close to signature of red dot



Properties:

- ✓ Efficient calculation
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- ✓ Stable
- ✓ Invariant under isometric deformations

Summary

Effective Shape Matching with the Heat Kernel Signature:

$$HKS(x, t) = k_t(x, x)$$

Models heat diffusion process on a shape

Only evaluated on the temporal domain

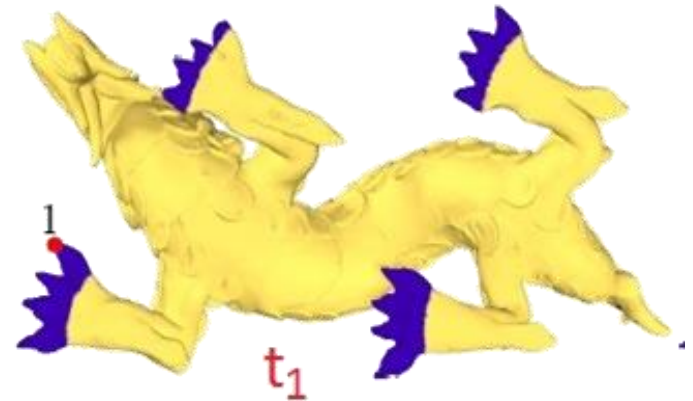
→ Efficient calculation, Concise

Time serves as scaling parameter

→ Multi-Scale

Preserves almost all of the intrinsic information about the geometry

→ Stable, Invariant under isometric deformations



Thank you for your attention

