Distinctive Local Features for 3D Point Cloud and Mesh Representation

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2. 3D Keypoint Detectors

3. 3D Local Feature Descriptors

4. Our Contributions
   4.1 RoPS: A Distinctive and Robust Feature Descriptor for 3D Local Surface Representation
   4.2 ARS: An Efficient Feature Descriptor for 3D Face Representation

5. Conclusion
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5. Conclusion
1.1 Point Cloud Acquisition

LiDAR

3D Scanners
Emerging 3D Cameras

More is coming....
1.2 Point Cloud Applications

- UAV & Robots
- Culture Heritage
- Remote Sensing & Mapping
- Multimedia & Biometrics
1.3 2D Images vs 3D Data

2D Images
- Grey Image / Coloured Image

3D Data
- Depth Image / Point Cloud / Mesh

<table>
<thead>
<tr>
<th></th>
<th>2D Images</th>
<th>3D Data</th>
</tr>
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<tbody>
<tr>
<td>Scale Changes</td>
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<td>Invariant</td>
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<td>Metric Space</td>
<td>Ambiguous</td>
<td>Unambiguous</td>
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<tr>
<td>Illumination Changes</td>
<td>Sensitive</td>
<td>Robust</td>
</tr>
<tr>
<td>Characteristics</td>
<td>Appearance</td>
<td>Shape</td>
</tr>
<tr>
<td>Data Structure</td>
<td>Structured</td>
<td>Unstructured (point cloud)</td>
</tr>
</tbody>
</table>
1.4 Representation of 3D Data

3D Data

- Depth Image
  - 2D image, projection on the imaging plane
- Point Cloud
  - unstructured 3D points, discrete sampling of a 3D surface
- Mesh
  - structured 3D points
  - vertices + faces
1.5 3D Local Feature Extraction

3D local feature extraction is a fundamental topic

- Keypoint Detection
- Local Feature Description
- Feature Correspondences / Classifiers
3D local feature extraction is a fundamental topic

- **Keypoint Detection**
  - Detect 3D points with rich information content (high saliency) from a point cloud/mesh, and determine the inherent scale of each keypoint.

---

### Feature Description

- **Feature Correspondences**

---

**Keypoint Detection**

**Feature Description**

**Feature Correspondences**
3D local feature extraction is a fundamental topic

- **Local Feature Description**
  - Encode the information of a local surface (around a keypoint) with a feature vector
1.5 3D Local Feature Extraction

Challenges

- Different Viewpoints
- Occlusion
- Clutter
- Noise
- Outliers
- Varying Mesh Resolutions (Point Densities)
Outline

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2.1 3D Keypoint Detector

The Task

- Detect 3D points with rich information content (high saliency) from a point cloud/mesh, and determine the inherent scale of each keypoint.

2.2 Taxonomy

Fixed-Scale Keypoint Detectors

- 3D Data
- Pruning
- Saliency-based NMS
- Fixed Scale
- Keypoints

Adaptive-Scale Keypoint Detectors

- 3D Data
- Embedding
- Scale-space
- Scale Selection
- Saliency-based NMS
- Pruning
- Adaptive Scale
- Keypoints with scale

2.3 Existing Work

- [Mokhtarian et al., IVC, 2001]
- [Yamany & Farag, TPAMI, 2002]
- [Pauly et al., CGF, 2003]
- [Li & Guskov, ESGP, 2005]
- [Gal & Cohen-Or, ACM TOG, 2006]
- [Matei et al., TPAMI, 2006]
- [Chen & Bhanu, TPAMI, 2007]
- [Akagunduz & Ulusoy, ICCV, 2007]
- [Novatnack & Nishino, ICCV, 2007]
- [Flint et al., IET-CV, 2008]
- [Castellani et al., CGF, 2008]
- [Hua et al., TVCG, 2008]
- [Zou et al., CAVW, 2008]
- [Unnikrishnan et al., CVPR, 2008]
- [Zhong, CVPRW, 2009]
- [Ho & Gibbins, IET-CV, 2009]
- [Hu & Hua, VC, 2009]
- [Sun et al., CGF, 2009]
- [Zaharescu et al., CVPR, 2009]
- [Zou et al., IEEE TVCG, 2009]
- [Hou & Qin, ECCV, 2010]
- [Knopp et al., ECCV, 2010]
- [Mian et al., IJCV, 2010]
- [Sipiran & Bustos, 2011]
- [Bariya et al., IJCV, 2012]
- [Zaharescu et al., IJCV, 2012]
- [Darom & Keller, IEEE TIP, 2012]
- [Tombari et al., IJCV, 2013]
- [Guo et al., TPAMI, 2014]
2.4 Intrinsic Shape Signatures (ISS)

- **Fixed-Scale**
  - Obtain three eigenvalues $\lambda_1, \lambda_2, \lambda_3$ by performing EVD on the scatter matrix of the points lying on a local surface

\[
\Sigma(p) = \frac{1}{N} \sum_{q \in N(p)} (q - \mu_p)(q - \mu_p)^T
\]

\[
\mu_p = \frac{1}{N} \sum_{q \in N(p)} q.
\]

- Prune points using

\[
\frac{\lambda_2(p)}{\lambda_1(p)} < Th_{12} \land \frac{\lambda_3(p)}{\lambda_2(p)} < Th_{23}
\]

- Define point saliency as

\[
\rho(p) = \lambda_3(p)
\]

2.5 KeyPoint Quality (KQS)

- **Fixed-Scale**
  - Rotate the local surface to align the point’s normal with the z-axis
  - Align the rotated local surface with its principal axes
  - Prune points using $\delta > t_1$, where
    $$\delta = \frac{\max(X) - \min(X)}{\max(Y) - \min(Y)}$$
  - Define keypoint quality as
    $$Q_k = \frac{1000}{n^2} \sum |K| + \max(100K) + |\min(100K)| + \max(10\kappa_1) + |\min(10\kappa_2)|.$$ 
    where $\kappa_1, \kappa_2$ and $K$ are maximum, minimum, and Gaussian curvatures, respectively.
  - Detect keypoints by comparing $Q_k$ to a threshold

2.6 MeshDOG

- **Adaptive-Scale**
  - (1) Scale Space Construction
    - Define a scalar field $f$ (photometric or geometric attribute) for each point
    - The scale space is built by progressive convolutions over $f$
      
      \[
      F_0 = f \\
      F_t = F_{t-1} \ast G_{\sigma(t)} \\
      t = \{1, 2, \ldots, s \cdot c\}
      \]

      where, the number of octaves $s = 3$, scales in each octave $c = 6$, the standard deviation of the Gaussian
      \[
      \sigma(t) = 2^{c-2} \left[\frac{t}{c}\right] e_{avg}
      \]
    - Calculate the Difference of Gaussian (DOG)
      \[
      L_t = F_t - F_{t-1}
      \]

A. Zaharescu, E. Boyer, R. Horaud, Keypoints and local descriptors of scalar functions on 2D manifolds. IJCV, 100: 78–98, 2012
2.6 MeshDOG

- **Adaptive-Scale**
  - *(2) Keypoint Detection*
    - **S1**: Select keypoint candidates as the local extrema over one ring neighbourhoods in the current and the adjacent scales
    - **S2**: Consider the top 5% of the maximum number of vertices according to their sorted magnitudes
    - **S3**: Keep the keypoint candidates that exhibit strong corner characteristics using Hessian matrix

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3.1 3D Local Feature Descriptors

The Task

- Encode the geometric information of a local surface (around a keypoint) with a feature vector
3.2 Taxonomy

3D Descriptors

- Signature based Descriptors
  - Spatial Distribution Histogram
- Histogram based Descriptors
  - Geometric Attribute Histogram
- Transform based Descriptors
  - Oriented Gradient Histogram

3.3 Existing Work

- [Stein & Medioni, TPAMI, 1992]
- [Chua & Jarvis, TPAMI, 1997]
- [Johnson & Hebert, TPAMI, 1999]
- [Sun & Abidi, ICCV, 2001]
- [Yamany & Farag, TPAMI, 2002]
- [Frome et al., ECCV, 2004]
- [Li & Guskov, ESGP, 2005]
- [Mian et al., TPAMI, 2006]
- [Chen & Bhanu, PAMI, 2007]
- [Malassiotis & Strintzis, TPAMI 2007]
- [Taati et al., ICCV 2007 & CVIU 2011]
- [Castellani et al., CFG, 2008]
- [Flint et al., IET-CV, 2008]
- [Hua et al., TVCG, 2008]
- [Novatnack & Nishino, ECCV, 2008]
- [Rusu et al., ICRA, 2009]
- [Hu & Hua, VC, 2009]

- [Masuda, CVIU, 2009]
- [Sun et al., CGF, 2009]
- [Zhong, ICCVW, 2009]
- [Zaharescu et al., CVPR, 2009]
- [Hou & Qin, ECCV, 2010]
- [Mian et al., IJCV, 2010]
- [Knopp et al., ECCV ,2010]
- [Tombari et al., ECCV, 2010]
- [Darom & Keller, TIP, 2012]
- [Kokkions et al., 2012]
- [Zaharescu et al., IJCV, 2012]
- [Bariya et al., IJCV, 2012]
- [Smeets et al., CVIU, 2013]
- [Guo et al. IJCV, 2013]
- [Tombari et al., CVIU, 2014]
- [Guo et al., TPAMI, 2014]
3.4 Spin Image

Spin Image Descriptor (PAMI 1999)

3.5 SHOT

SHOT Descriptor (ECCV 2010, CVIU 2014)

- Construct an LRF for a keypoint
- Divide the neighbourhood space into 3D volumes
- Generate a local histogram by accumulating the number of points according to the angles between the normal at the keypoint and these at the neighbouring points
- Concatenate local histograms to form SHOT descriptor

3.6 MeshHOG

MeshHOG Descriptor (IJCV 2012)

- Construct an LRF for a keypoint using the surface normal and tangent plane.
- Project the gradient vectors onto 3 planes associated with the LRF, and divide each plane into 4 polar slices.
- Obtain an 8-bin histogram for each polar slice using the orientations of the gradients.
- Generate the MeshHOG descriptor by concatenating all histograms.

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4.1.1 Motivation

- **Motivation**
  - Most of the existing feature descriptors suffer from either low descriptiveness or weak robustness.
  - Many descriptors were extended from their 2D counterparts, they did not fully consider the intrinsic 3D information.
    - SIFT -> 2.5D SIFT, SI-SIFT, meshSIFT, SHOT
    - SURF -> 3D SURF
    - HOG -> MeshHOG

- **Our Goal**
  - Design a 3D local feature descriptor which is highly descriptive, robust, compact, and invariant to rigid transformations.
4.1.2 A Feature Description Framework

3D Local Feature Description Framework

- Pose Normalization
- Multi-view Information Representation
4.1.2 A Feature Description Framework

Multi-view Information Representation

- Viewpoint Setup
- Multi-view Information Generation
- Multi-view Feature Extraction
- Multi-view Feature Fusion
4.1.3 RoPS Feature Descriptor

Part 1 - Local Reference Frame Construction

- Coordinate Axis Construction

\[
\mathbf{C}_i = \frac{\int_0^1 \int_0^{1-s} (\mathbf{p}_i(s, t) - \mathbf{p})(\mathbf{p}_i(s, t) - \mathbf{p})^T \, dt \, ds}{\int_0^1 \int_0^{1-s} \, dt \, ds}
\]

\[
\mathbf{C}_i = \frac{1}{12} \sum_{j=1}^{3} \sum_{k=1}^{3} (\mathbf{p}_{ij} - \mathbf{p})(\mathbf{p}_{ik} - \mathbf{p})^T
\]

\[
+ \frac{1}{12} \sum_{j=1}^{3} (\mathbf{p}_{ij} - \mathbf{p})(\mathbf{p}_{ij} - \mathbf{p})^T.
\]

\[
\mathbf{C} = \sum_{i=1}^{N} w_{i1}w_{i2} \mathbf{C}_i
\]

\[
\mathbf{CV} = \mathbf{EV}
\]
4.1.3 RoPS Feature Descriptor

Part 1 - Local Reference Frame Construction

- Sign Disambiguation

\[ \tilde{v}_1 = v_1 \cdot \text{sign}(h) \]

\[ h = \sum_{i=1}^{N} w_{i1} w_{i2} \left( \int_{0}^{1} \int_{0}^{1-s} (p_i(s, t) - p) v_1 \, dt \, ds \right) \]

\[ = \sum_{i=1}^{N} w_{i1} w_{i2} \left( \frac{1}{6} \sum_{j=1}^{3} (p_{ij} - p) v_1 \right). \]

\[ \tilde{v}_3 = v_3 \cdot \text{sign} \left( \sum_{i=1}^{N} w_{i1} w_{i2} \left( \frac{1}{6} \sum_{j=1}^{3} (p_{ij} - p) v_3 \right) \right) \]
4.1.3 RoPS Feature Descriptor

3D Local Feature Description Framework

- Pose Normalization
- Multi-view Information Representation
4.1.3 RoPS Feature Descriptor

Part 2 - Local Surface Description

- (a) Object
- (b) Local surface $Q'$
- (c) Rotated surface $Q'(\theta_k)$
- (d) Projection
- (e) Distribution matrix $D$
- (f) Statistics $\{\mu_{mn}, e\}$
- (g) Sub-feature $f_x(\theta_k)$
4.1.3 RoPS Feature Descriptor

Part 2 - Local Surface Description

\[ \mu_{mn} = \sum_{i=1}^{L} \sum_{j=1}^{L} (i - \bar{i})^m (j - \bar{j})^n \mathbf{D}(i, j) \]

\[ e = -\sum_{i=1}^{L} \sum_{j=1}^{L} \mathbf{D}(i, j) \log(\mathbf{D}(i, j)) \]

\[ f = \{ f_x(\theta_k), f_y(\theta_k), f_z(\theta_k) \}, \quad k = 1, 2, \ldots, T \]

---

1. $\mu_{02}, \mu_{11}, \mu_{20}$
2. $\mu_{02}, \mu_{11}, \mu_{20}, \mu_{03}, \mu_{12}, \mu_{21}, \mu_{30}$
3. $\mu_{02}, \mu_{11}, \mu_{20}, \mu_{03}, \mu_{12}, \mu_{21}, \mu_{30}, \mu_{04}, \mu_{13}, \mu_{22}, \mu_{31}, \mu_{40}$
4. $\mu_{02}, \mu_{11}, \mu_{20}, \mu_{03}, \mu_{12}, \mu_{21}, \mu_{30}, \mu_{04}, \mu_{13}, \mu_{22}, \mu_{31}, \mu_{40}, e$
5. $\mu_{11}, \mu_{21}, \mu_{12}, \mu_{22}$
6. $\mu_{11}, \mu_{21}, \mu_{12}, \mu_{22}, e$
7. $\mu_{11}, \mu_{21}, \mu_{12}, \mu_{22}, \mu_{31}, \mu_{13}$
8. $\mu_{11}, \mu_{21}, \mu_{12}, \mu_{22}, \mu_{31}, \mu_{13}, e$
4.1.4 Why RoPS Works?

Intuitive Justification

- **Descriptiveness**
  - Encode the “complete” information of the local surface from various viewpoints through rotation

- **Invariance**
  - The unambiguous and stable LRF

- **Robustness to Noise**
  - Low-order statistics (moments) of the distribution matrices

- **Robustness to Varying Mesh Resolutions:**
  - The 2D projection planes are sparsely partitioned
  - Its LRF is derived by calculating the scatter matrix of all the points lying on the local surface rather than just the vertices

- **Compactness**
  - Projection: 3D -> 2D
  - Statistics: 2D matrix -> 1D vector
4.1.5 Performance (Bologna Dataset)

Robustness to Noise

- Noise free
- Noise std 0.1mr
- Noise std 0.3mr
- Noise std 0.5mr
4.1.5 Performance (Bologna Dataset)

Robustness to Varying Mesh Resolution

Decimation 1/2

Decimation 1/4

Decimation 1/8

Noise std 0.1mr & decimation 1/2
### 4.1.6 Performance (PHOTOMESH Dataset)

#### RoPS

<table>
<thead>
<tr>
<th>Transform</th>
<th>Strength</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
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<td>Color noise</td>
<td>0.00</td>
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<td>Color shot noise</td>
<td>0.00</td>
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<td>Geometry noise</td>
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<td>Geometry shot noise</td>
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<td>Rotation</td>
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<tr>
<td>Scale</td>
<td>0.00</td>
</tr>
<tr>
<td>Local scale</td>
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</tr>
<tr>
<td>Sampling</td>
<td>0.01</td>
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<tr>
<td>Holes</td>
<td>0.01</td>
</tr>
<tr>
<td>Marco-holes</td>
<td>0.00</td>
</tr>
<tr>
<td>Topology</td>
<td>0.01</td>
</tr>
<tr>
<td>Isometry + noise</td>
<td>0.02</td>
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<tr>
<td>Average</td>
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</tr>
</tbody>
</table>

#### MeshHOG (IJCV 2012)

<table>
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<th>Transform</th>
<th>Strength</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>Color noise</td>
<td>0.00</td>
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<tr>
<td>Color shot noise</td>
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<td>Geometry noise</td>
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<td>Marco-holes</td>
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<td>Isometry + noise</td>
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<tr>
<td>Average</td>
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</table>
4.1.7 Applications

3D Object Recognition

3D Modeling

(a) Input Meshes
(b) Shape Growing
(c) Multi-view Registration
(d) 3D Models
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5. Conclusion
4.2.1 Motivation

Motivation

- Many existing 3D face recognition approaches are very time consuming
  - They rely on surface registration (e.g., ICP) or complex feature matching
- 3D face recognition accuracy is highly challenged by expression variations.

Our Goal

- Design a 3D local feature descriptor which is highly descriptive, efficient, and robust to facial expressions.
4.2.2 Angular Radial Signature

Stage 1 - ARS Feature Generation

- ARS features are generated for each face
- Mask is used for fast computation
4.2.2 Angular Radial Signature

Stage 2 - KPCA Mapping

- KPCAs are trained to transform the ARSs to mid-level feature representations
- Address the linearly inseparable problem by transforming the ARSs to a high-dimensional nonlinear space
- All mid-level features are concatenated into a single feature. Multiple KPCA models results in a more discriminative mapping
- Polynomial, sigmoid, radial basis function

\[
X = [x_1 \ldots x_M] \in \mathbb{R}^{D \times M} \\
K_{ij} = k(x_i, x_j) = (\varphi(x_i) \cdot \varphi(x_j)), \quad i, j = 1 \ldots M \\
\varphi : \mathbb{R}^D \to \mathbb{F} \\
M \varphi A = K a
\]
4.2.3 Face Recognition Algorithm

Stage 2 - SVM Classification

- Mid-level features are combined to a final feature vector and fed into an SVM for face recognition
  
  \[
  \min_{w,b,\xi} \left( \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \right) 
  \]
  
  s.t. \quad y_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i

- Linear kernel based SVM is used
  
  - ARS features have already been non-linearly mapped using KPCA
  
  - Linear kernel does not require any parameter selection
4.2.4 Experimental Results

Face Identification Task

- (a) CMC on FRGC v2.0 dataset: R1-IR 93.4%
- (b) CMC on SHREC2008 dataset: R1-IR 90.7%
4.2.4 Experimental Results

Face Verification Task

- (a) ROC on FRGC v2.0 dataset: VR@0.1\%FAR 97.8\%
- (b) ROC on SHREC2008 dataset: VR@0.1\%FAR 88.5\%
4.2.4 Experimental Results

Computational Efficiency

- Implemented in Matlab and C++
- Tested on a PC with an Intel Core2 Quad CPU and 8GB RAM

<table>
<thead>
<tr>
<th>Step</th>
<th>Number of faces</th>
<th>Individuals</th>
<th>Time cost (s)</th>
</tr>
</thead>
<tbody>
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<td>1</td>
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<tr>
<td>ARSs extraction</td>
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<td>Training</td>
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<td>466</td>
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<td></td>
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<td>KPCA</td>
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- Comparison

<table>
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<tr>
<th>Method</th>
<th>Time</th>
<th>Method</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kakadiaris et al.</td>
<td>744.2s</td>
<td>Mian et al.</td>
<td>6388s</td>
</tr>
<tr>
<td>Faltemier</td>
<td>1,711,664.6s</td>
<td>Wang et al.</td>
<td>1054s</td>
</tr>
<tr>
<td>Ballihi et al.</td>
<td>506,057.4s</td>
<td>The proposed</td>
<td>6.07s</td>
</tr>
</tbody>
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Conclusion

We Proposed

- RoPS: A highly distinctive and robust feature descriptor for 3D local surface representation
- ARS: A highly efficient feature descriptor for 3D face representation

Open Issues

- Feature extraction by the fusion of photometric and geometric information
- Feature extraction via machine learning (deep learning)
- Lightweight 3D local features
Collaborators

Y. Guo @ NUDT
M. Bennamoun @ UWA
Y. Lei @ SCU
M. Lu @ NUDT
J. Wan @ NUDT
F. Sohel @ UWA
Thank You

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