# HIGH-ORDER LOCAL NORMAL DERIVATIVE PATTERN (LNDP) FOR 3D FACE RECOGNITION



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METHODS CATEGORIZATION
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Face recognition: global and local feature-based Methods Local descriptors: prominent points, patches or regions of the face to handle facial expression, occlusion, and missing

data

### **PRE-PROCESSING**

- Remove spike and noises using median filter
- Hole filling by fitting square surface

Algorithm 1 n <sup>th</sup> -order LNDP	For a r
Input: 3D face data P	
1: for each point in $P$ do	$N'_{45^\circ}$
2: Calculate normal components $(N_x, N_y, \text{ and } N_z)$	)
3: end for	The se
4: for each N do	
5: Divide into $10 \times 8$ patches	
6: end for	
7: for $alpha = 0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ}$ do	Binary
8: for each patch do	is equ

**PROPOSED LNDP** 

For a normal component the first-order derivatives:

 $N'_{0^{\circ}}(P_{0}) = N(P_{0}) - N(P_{4}) \qquad N'_{90^{\circ}}(P_{0}) = N(P_{0}) - N(P_{2})$  $N'_{45^{\circ}}(P_{0}) = N(P_{0}) - N(P_{3}) \qquad N'_{135^{\circ}}(P_{0}) = N(P_{0}) - N(P_{1})$ 

The second-order normal local derivative pattern:

 $LNDP_{\alpha}^{2}(P_{0}) = (f(N_{\alpha}'(P_{0}), N_{\alpha}'(P_{1})), f(N_{\alpha}'(P_{0}), N_{\alpha}'(P_{2}))...,$  $f(N_{\alpha}'(P_{0}), N_{\alpha}'(P_{8})))$ 

Binary coding function s equal to 0 if

 $f(N'_{\alpha}(P_0), N'_{\alpha}(P_i))$  $N'_{\alpha}(P_0) N'_{\alpha}(P_i) > 0$ 

- Nose detection by curvature-based method, and region of interest (ROI) cropping
- Pose correction (the iterative closest point (ICP))

### SURFACE NORMAL

 $P = [p_1, p_2, ..., p_n]^T, p_i \in R^3 \quad p_i = [p_{ix}, p_{iy}, p_{iz}]^T$  $n_i = [n_{ix}, n_{iy}, n_{iz}]^T Q_i = [q_{i1}, q_{i2}, ..., q_{il}]^T \min A(p_i, Q_i, n_i)$ 



Range image, normal component x, normal component y, and normal component z

## LOCAL DERIVATIVE PATTERN

LDP: encoding directional pattern features

- for each pixel in patch of N do
   Apply Equation (★)
- end for
- Encode *LNDP* using Equation (\*\*) Histogram construction
- 14: end for

9:

10:

11:

12:

13:

- 15: Concatenate the histogram for different patches16: end for
- 17: Concatenate the histogram for different  $\alpha$ 18: return  $HLNDP_x^n$ ,  $HLNDP_y^n$ ,  $HLNDP_z^n$

The decimal value of the descriptor:  $LNDP^{n}_{\alpha}(P_{0}) = \sum LNDP^{n}_{\alpha}(P_{0}) \times 2^{l-1} \star \star$ Similarity:

$$S(H_G, H_Q) = \sum_{i=1}^{C} \min(H_G(i), H_Q(i))$$

and equal to 1 if

### $N'_{\alpha}(P_0).N'_{\alpha}(P_i) <= 0.$

#### nth- order of LNDP:

 $LNDP_{\alpha}^{n}(P_{0}) = (f(N_{\alpha}^{n-1}(P_{0}), N_{\alpha}^{n-1}(P_{1})), f(N_{\alpha}^{n-1}(P_{0}), \star N_{\alpha}^{n-1}(P_{2}))..., f(N_{\alpha}^{n-1}(P_{0}), N_{\alpha}^{n-1}(P_{8})))$ 



HLNDP for x, y, and z facial normal components

## **EXPERIMENTAL RESULTS**

Different orders on FRGC v2.0 DB

CMC (score-level fusion third-order LNDP)







#### Comparison of LBP-based methods

Descriptor	RR1 (FRGC v2.0)	Methods	RR1 (FRGC v2.0)	RR1 (Bosphorus)									
DepthLBP	86.2%	MS-eLBPDFs [1]	97.6%	97%									
DLDP <sup>3</sup>	89.08%	V-LBP [2]	94.89% (900/150)	-									
$LNDP_x^3$	92.53%	MSMC-LNP [3]	96.3%	95.4% (2797/105)									
$LNDP_y^3$	91.18%	DLBP [4]	90%	90%									
$LNDP_z^3$	96.04%	Region-based-eLBP [5]	97.8%	_									
$LNDP_{xyz}^3$	98.1%	$LNDP_{xyz}^3$	98.1%	97.3%									
	3       89.08%       V-LBP [2]       94.89% (900/150)       -         3       92.53%       MSMC-LNP [3]       96.3%       95.4% (2797/105)         3       91.18%       DLBP [4]       90%       90%         3       96.04%       [5]       -       -         3       98.1%       LNDP <sup>3</sup> <sub>XYZ</sub> 98.1%       97.3%         Conclusion												
High-order LNDP (more detailed distinct information from the 3D facial image) is proposed. The score-level fusion (LNDPx, LNDPy, and LNDPz) is applied.													

α=1	350			Tı	<b>α</b> =1	1350			T2	<u>α=1</u> b)	1350			T3	<b>α</b> =1	1350			14
	17	10	15			17	10	15			<b>F</b> 7	го	<b>F</b> 5			17	10	15	
	$\mathbf{p}_{2}$	D,	<mark>ک</mark> ر			$\mathbf{D}_{2}$	<mark>ک</mark> ر	$\mathbf{D}_{c}$			D-	D,	D-			$\mathbf{D}_{2}$	D,	Ρc	
	P <sub>8</sub>	Ρ <sub>0</sub>	$P_4$			P8	• P <sub>0</sub>	$P_4$		Pi	$P_8$	P <sub>0</sub>	<b>P</b> <sub>4</sub>			`P <sub>8</sub>	<b>`</b> P <sub>0</sub>	<b>`</b> P <sub>4</sub>	

(a) 8-neighborhood around P0 (b) 32 templates for  $\alpha = 0, 45, 90, 135$ 

The black and dashed red lines represent two - different templates:

T1(i =1, 5), T2(i =2, 6), T3(i =3, 7), and T4(i =4, 8)

#### References

The algorithm is training free and computationally efficient.
The proposed descriptor can be used in 3D object recognition as well.

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