

## Cross Diffusion on Multi-Hypergraph for Multi-Modal 3D Object Recognition



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## **3D Object Recognition**



# **3D Object Representation**

#### **Multi-modal Data**

#### **View-based Representation**



**Point Cloud** 



View



**MVCNN** 



Volumetric



Mesh

FCN + CNN + View Proling FCN + CNN + View Pooling i Group FCN + CNN + View Pooling Group Group FCN + CNN + View Pooling Group FCN + CNN + View Pooling Group FCN + CNN + View Pooling Group Group FCN + CNN + View Pooling FCN + View Pooling 

GVCNN

# **3D Object Representation**

#### **Multi-modal Data**



**Point Cloud** 



View

#### **View-based Representation**



(a) MVCNN

Group

**Final View** 

**Raw View** 



Volumetric



Descriptors Descriptors Descriptors FCN CNN View Shape CNN Descriptor ECN Viev Group Pooling FCN CNN Fusion Ben TV Sta Cup FCN Poolin CNN Weight

(b) GVCNN

## **3D Object Representation**



# How to combine multiple 3D representations towards better 3D object recognition performance?

**Challenge 1**: Exploit correlation among multi-modal data **Challenge 2**: Consider multi-modal data simultaneously during multi-modal fusion process

## **Related Work**

## **3D Object Representations**

#### **Volumetric Data**

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[Wu et al. 2015] (3D ShapeNets) [Maturana et al. 2015] (VoxNet) [Wang et al. 2017] (O-Net) [Tatarchenko et al. 2017] (OGN)



Point Cloud Data

[Qi et al. 2017] (PointNet) [Qi et al. 2017] (PointNet++) [Fan et al. 2017] (PointSetGen)

### How to combine them?



[Su et al. 2015] (MVCNN) [Kalogerakis et al. 2016] [Guo et al. 2016] [Feng et al. 2018] (GVCNN)

View Data



#### Mesh Data

. . . . . .

[Defferard et al. 2016] [Henaff et al. 2015] [Yi et al. 2017]

## **Related Work**



Multi-Hypergraph Learning [Gao et al. TIP'12]

#### **Disadvantages:**

- 1. The computational cost is very high.
- 2. Multi-modal data are only considered in the fusion part.

## **Motivations**

# How to combine multiple 3D representations towards better 3D object recognition performance?

**Challenge 1**: Exploit correlation among multi-modal data **Challenge 2**: Consider multi-modal data simultaneously during multi-modal fusion process

Task 1: Employ multi-hypergraph structure to formulate the correlation among 3D objects Task 2: Conduct cross diffusion process on the multihypergraph structure

## Framework



# **Correlation Modelling**

#### **Correlation Modelling**



Hypergraph

 $\mathcal{G} = (\mathcal{V}, \mathcal{E}, W)$ 

Each vertex represents an object.

#### Example



# **Diffusion Process on Single Hypergraph**



#### The diffusion process is much faster than traditional methods.

# **Cross Diffusion Process on Multi-Hypergraph**



#### **Advantages:**

- 1. The multi-hypergraph structure can model the high-order correlation among multi-modal data.
- 2. The cross diffusion process can combine multi-modal data effectively.
- 3. The cross diffusion process is very fast.

# **Experiments**



#### Two kinds of 3D features:

- Multi-View Convolutional Neural Networks (MVCNN)
- Group-View Convolutional Neural Networks (GVCNN)

#### State-of-the-art methods

- MVCNN [1] and GVCNN [2]
- MVCNN+HL and GVCNN+HL
- MVCNN+GVCNN+HL
- MVCNN+GVCNN+MHL [3]
- Cross Diffusion on Multi-Hypergraph (CDMH)
- [1] Su et al. Multi-View Convolutional Neural Networks for 3D Shape Recognition. CVPR'15
- [2] Feng at al. GVCNN: Group-View Convolutional Neural Networks for 3D Shape Recognition. CVPR'18
- [3] Gao et al. 3D Object Retrieval and Recognition with Hypergraph Analysis. TIP'12

## **Experimental Results**

#### **Classification Accuracy**

Method	ModelNet40	NTU
MVCNN	90.10%	79.89%
GVCNN	93.10%	82.30%
MVCNN+HL	90.68%	79.89%
GVCNN+HL	92.14%	82.84%
MVCNN+GVCNN+HL	93.23%	80.43%
MVCNN+GVCNN+MHL	96.19%	83.38%
CDMH	96.76%	$\boldsymbol{84.45\%}$
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Time Cost		
Method	ModelNet40	NTU
MVCNN+GVCNN+MHL	869.4s	$6.652 \mathrm{s}$

The speed is increased by **400** times.

2.233s

0.332s

CDMH

Our proposed method can achieve better performance and faster speed than state-of-the-art methods.

## **Experimental Results**

#### **Confusion Matrix**



## **On Hypergraph Construction and Diffusion Process**

#### **On Hypergraph Construction**



Our proposed method can achieve stable performance with different parameters and converge fast.

# Conclusion

- We propose a cross diffusion method on multi-hypergraph for multi-modal 3D object recognition.
- The proposed method is more effective and efficient than the state-ot-the-art methods.
- The proposed method is a general framework which can be used in other applications with multi-modal data.





Medical Image Analysis



Social Media Analysis

## References

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# **Thanks!**

# Conclusion

- We propose a cross diffusion method on multi-hypergraph for multimodal 3D object recognition.
- The proposed method is more effective and efficient than the state-ot-the-art methods.
- The proposed method is a general framework which can be used in other applications with multi-modal data.

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Medical Image Analysis

Social Media Analysis

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