ISTITUT NATIONAL DE L'INFORMATION GÉOGRAPHIQUE ET FORESTIÈRE

# Semantic 3D building model evaluation

Oussama Ennafii

Univ. Paris Est, LaSTIG STRUDEL, IGN, ENSG

October 17, 2018



## Introduction

#### Context: 3D model vs. 3D mesh

 $\blacktriangleright$  3D urban model  $\leftrightarrow$  polyhedral surface representing a building.





#### Context: 3D model vs. 3D mesh

 $\blacktriangleright$  3D urban model  $\longleftrightarrow$  polyhedral surface representing a building.

 $\blacktriangleright$  a 3D model facet  $\longleftrightarrow$  an architectural feature.



#### Context: 3D model vs. 3D mesh

 $\blacktriangleright$  3D urban model  $\longleftrightarrow$  polyhedral surface representing a building.

 $\blacktriangleright$  a 3D model facet  $\longleftrightarrow$  an architectural feature.











#### Motivation

- Automatic urban modeling: an active research area (Musialski et al., 2012);
- Results seamless but lack generality and often erroneous (Rottensteiner et al., 2014);



#### Motivation

- Automatic urban modeling: an active research area (Musialski et al., 2012);
- Results seamless but lack generality and often erroneous (Rottensteiner et al., 2014);
  - $\longrightarrow$  labourious manual corrections.

#### Motivation

- Automatic urban modeling: an active research area (Musialski et al., 2012);
- Results seamless but lack generality and often erroneous (Rottensteiner et al., 2014);
  - $\longrightarrow$  labourious manual corrections.
- Urban 3D model semantic diagnostic not well studied (Nguatem and Mayer, 2017);



#### 



- Goal → Detect and describe semantic errors that affect building 3D models.
- Semantic errors independent from reconstruction methods and urban scenes.



- Goal → Detect and describe semantic errors that affect building 3D models.
- Semantic errors independent from reconstruction methods and urban scenes.
- **Transferability**, and hence scallability, of the evaluation method.









Change detection;

▶ Urban models correction;



#### Change detection;

Urban models correction;

Urban reconstruction method evaluation;





#### Change detection;

Urban models correction;

Urban reconstruction method evaluation;

Crowd reconstruction quality assessment.





# Methodology

#### Main ideas behind our approach

Compile errors that affect building models in a taxonomy;



#### Main ideas behind our approach

Compile errors that affect building models in a taxonomy;

► Evaluation at building level ⇒ formulated as a supervised classification problem;

#### Main ideas behind our approach

Compile errors that affect building models in a taxonomy;

► Evaluation at building level ⇒ formulated as a supervised classification problem;

Study in a 2.5D overhead (aerial) modeling setting.



Two criteria determine the taxonomy structure:





Two criteria determine the taxonomy structure:

the Level of Detail (LoD);





Two criteria determine the taxonomy structure:

the Level of Detail (LoD);

▶ the *finesse*: the semantic evaluation level.





Two criteria determine the taxonomy structure:

the Level of Detail (LoD);

▶ the *finesse*: the semantic evaluation level.

#### Definition

An error is of maximal *finesse*  $\Leftrightarrow$  it corresponds, semantically, to a unitary action required to correct the model. The error is called *atomic*.



#### Error taxonomy (finesse = 0)



#### Error taxonomy (finesse = 1)



#### Error taxonomy (finesse = 2)





### Error taxonomy (finesse = 2)





#### Error taxonomy (finesse = 3)





#### Building atomic errors: 2.5D overhead reconstruction case



(a) Under segmentation



(b) Over segmentation



(C) Imprecise border



(d) Inaccurate topology





#### Error taxonomy (finesse = 3)





#### Facet atomic errors: 2.5D overhead reconstruction case







(b) Over segmentation



(c) Imprecise borders



(d) Inaccurate topology



(e) Imprecise geometry



#### The evaluation pipeline sketch







#### Geometric features



IGN



#### Height-based features





#### Image-based features



- (a) A building projection and the corresponding orthoimage.
- (b) For each facet edge, the cosine similarity is computed between its normal and the image gradient, on each intersecting pixel (in green).





. . . .

### Experiments

																	-J		

### Results using all features

	Elancourt	Nantes	Paris 13
# samples	2009	748	478

Dataset statistics





#### Results using all features

	Elancourt	Nantes	Paris 13
# samples	2009	748	478

#### Dataset statistics

	Elancourt (1	0-cross val.)	Elancourt –	Nantes	Elancourt -	> Paris 13
	Recall	Prec.	Recall	Prec.	Recall	Prec.
BOS	90.83	76.14	93.12	42.61	96.53	43.82
BUS	39.32	71.81	8.82	66.67	0	_
BlmB	16.75	68.0	2.02	33.33	0	_
BInT	11.11	91.67	0.88	100	3.95	50.0
FOS	98.91	98.84	98.33	97.92	97.19	97.58
FUS	1.27	66.67	13.81	63.04	8.36	95.83
FImB	7.42	100	46.34	65.52	11.80	60.71
FImT	3.33	100	9.09	100	0	0
FIG	79.02	71.82	94.17	70.70	86.16	88.47

Test results using Random Forest (max depth = 4 & #trees = 1000) trained on Elancourt.



#### Some failure cases on Elancourt

6	in the second				0			$\langle \rangle$		in the second	
Errors			Errors			Errors			Errors		
	G. T.	Pred.		G.T.	Pred.		G. T.	Pred.		G.T.	Pred.
BOS	×	<ul> <li>Image: A second s</li></ul>	BUS	×	<ul> <li>Image: A second s</li></ul>	BOS	<ul> <li>Image: A set of the set of the</li></ul>	<ul> <li>Image: A second s</li></ul>	BOS	<ul> <li>Image: A set of the set of the</li></ul>	×
Valid	1	×	FIG	<ul> <li>✓</li> </ul>	×	FUS	1	×	FOS	<ul> <li>✓</li> </ul>	×
			FOS	1	×				BUS	1	×
									BImB	<ul> <li>Image: A second s</li></ul>	<ul> <li>Image: A second s</li></ul>





## Conclusion

																	·		1	

#### Conclusion & Perspectives

Flexible, robust and hierarchical taxonomy;

**Fast, lightweight and modular** pipeline for model evaluation;

Baseline for geometric, image-based and height-based features;





#### Conclusion & Perspectives

Flexible, robust and hierarchical taxonomy;

**Fast, lightweight and modular** pipeline for model evaluation;

Baseline for geometric, image-based and height-based features;

Future work:

▶ Dataset augmentation → Simulate errors from the taxonomy based on reference data;

 $\blacktriangleright$  Extend to richer features  $\longrightarrow$  Graph kernels, deep learning.





IGN INSTITUT NATIONAL DE L'INFORMATION GÉOGRAPHIQUE ET FORESTIÈRE

