AUTOMATIC BUILDING RECONSTRUCTION FROM A DIGITAL ELEVATION MODEL AND CADASTRAL DATA : AN OPERATIONAL APPROACH

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ABSTRACT:

In this paper, we tackle the problem of automatic building reconstruction using digital elevation model and cadastral data. We aim at massive production of 3D urban models and present thus an algorithm, that is an adaptation of a more general and semi-automatic strategy to an operational context where robustness is essential. We present two approaches relying on two different techniques for non vertical planes extraction using constraints inferred by cadastral limits. The first one consists in inferring planar primitives by estimating only two parameters for each building : the height of gutter and the slope of roofs. The other idea is to extract planar primitives directly from the cadastral limits and from the DEM, using a robust RANSAC estimation algorithm. The results of an evaluation carried out on 620 buildings on a dense urban centre are promising and enables to compare both approaches.

1 INTRODUCTION

1.1 Context and objectives

In this article, we deal with automatic building reconstruction from aerial images to define a production line for massive production of 3D urban models. Real time, robustness and automation are then essential criteria.
We propose here to adapt a generic reconstruction algorithm (Taillandier and Deriche, 2004) to an operational context. The general algorithm implements a hypothesize-and-verify strategy where buildings are modeled in a very general way as any polyhedral shapes with no overhang. This algorithm only uses aerial images but some limitations prevent its direct use in a context of massive production of 3D models where robustness of building reconstructions is more important than generality. Especially, to overcome the weakness of primitives detector, we now propose to use cadastral limits where polygones define buildings outlines and a digital elevation model. We will present the necessary adaptations to implement this algorithm using these data in the context of an operational production line where real-time and automation are key issues.

1.2 State of the art

Automatic building reconstruction has interested the community for more than ten years and numerous works have focussed on this subject. Several strategies in various context have appeared : data-based or model-based approaches, in a stereoscopic context or from multiple aerial images, with or without external data.
Stereoscopy allows to obtain a reliable 3D information but there can be occlusions problems in a dense urban environment. Thus, in this context, in order to overcome the lack of information, methods often implement model-based approaches ((Cord et al., 2001), (Paparoditis et al., 1998)). They consequently suffer from a lack of generality.
Multiscopy allows to avoid occlusions problems, therefore, methods are more general and implements data-based strategy. Most of the developed approaches use only one kind of primitives (corners for example for (Heuel et al., 2000)). The major drawback of these methods is their lack of robustness. In (Baillard and Zisserman, 1999), for instance, the method described allows to produce generic models from aerial images. It is based on the detection of 3D segments and then on facets detection around these segments by correlation. Planes intersection allows to define roofs. The main drawback of this method is the absence of under-detection handling and its lack of robustness making it not adapted to a massive production environment.
Cadastral limits allow to add strong information on structures and have been studied for building reconstruction. (Flamanc et al., 2003) developed a model approach using cadastral limits to deduce possible skeleton of the building and then a possible models library. The principal disadvantage of this approach is its lack of generality. In (Vosselman and Suveg, 2001), authors propose to segment the cadastral parcel in elementar rectangles. Each rectangle can represent an elementar form among three possible shapes. The set of possible models is built from the collection of possible segmentations of the parcel. This method can provide robust models but it is not adapted to our context due to the high number of generated hypotheses and therefore the induced computing time for construction and evaluation of these hypothesis.
The approach of (Jibrini et al., 2000) utilizes cadastral limits so as to constraint planes search by a Hough transform technique. The enumeration algorithm is very interesting, the general strategy of this article is an extension of it. However, planes extraction with Hough transform gives a lot of over detections and leads to a combinatory explosion and then to a lack of robustness of the reconstructed models, which penalises this algorithm.

1.3 Structure of the article

We first describe a general algorithm of building reconstruction (part 2.1). We then detail the adaptations for its use with cadastral maps : on the one hand by simulating planar primitives (part 2.2.1), on the other hand, by extracting planar primitives with RANSAC algorithm (part 2.2.2).
We will present the results of an evaluation of these two methods led on the urban center of Amiens. Finally, we conclude and present future work.

2 BUILDING RECONSTRUCTION

2.1 Original algorithm : polyedral model without overhang

The complete description of this general algorithm can be found in (Taillandier and Deriche, 2004).

Reconstruction is performed solely from aerial images without any cadastral information. However as it is shown afterwards, user-interaction is still needed in the focusing step. A building is modeled as a polyhedral form, without overhang and whose outline is constituted with vertical planes. This very generic modeling allows to represent almost all of the buildings in urban area.

We briefly sum up the general methodology. The main steps are shown on an example on figure 1. For each building or group of buildings, the operator manually selects a focusing area and a ground altitude (the maximum altitude is automatically deduced), therefore delineating a volume in which reconstruction should be performed. Reconstruction is then achieved in a four-step algorithm.

First, planar primitives (plane facets and oriented facades) and 3D segments are automatically detected in the volume.

In the second step, a 3D graph is generated from the intersection of all the detected planar primitives (facades and non-vertical planes). After simplifications in this graph, it is proven that the search for all possible shapes of buildings is equivalent to the search for maximal cliques in an appropriate graph. All possible models of buildings are thus enumerated in this second step leading to a set Γ of possible solutions.

In the third step, the best model $\widehat{M}$ is then chosen in the entire set of possible solutions Γ by bayesian modeling (equation 1) by taking into account the adequation of the model with observations D ($P(D/M)$ term) and simplicity of the form ($P(M)$ term).

$$\widehat{M} = \arg\max_{M\in\Gamma}(P(M/D)) = \arg\max_{M\in\Gamma}\{P(D/M)\cdot P(M)\} \tag{1}$$

The term related to the adequacy of the model with the data, $P(D/M)$, allows to take into account the adequation of the model with external data (detected segments, over-ground mask, images ...). The term related to complexity form probability, $P(M)$, is inspired by the Shannon relation and is linked to the description length $\mathcal{L}(M)$ of the model (that takes into account for example topological and geometrical informations).

$$P(M) = C \cdot \exp^{-\frac{\mathcal{L}(M)}{\beta}} \tag{2}$$

The parameter β allows to adjust the data term and the complexity term, C is a normalization term common to all models and then omitted afterwards.

The final step of the algorithm consists in automatic application of geometrical constraints on the chosen model.

This general algorithm allows to reconstruct very complex buildings, buildings with internal facades and even several buildings on the same focusing area. However, in an operational context and in dense urban environment, some limitations are very restrictive : focusing on an area is a manual action and the exhaustive exploration of all possible models can involve combinatory problems since the maximal clique exploration is a NP problem. Finally, even if the algorithm can manage errors of the primitives detector, this primitives extraction is only made from images : quality of primitives geometry strongly depends on images quality and errors of primitives extraction are mostly the cause of false reconstructions.

2.2 Adaptation for an operational context

The objective is to adapt the former algorithm to integrate it in an operational software. Whereas generality was previously favoured, we now aim at more robustness with a real-time constraint.

In this context, cadastral data bring useful information. The outlines of the buildings are indeed essential to solve some problems: focusing area delineation is automatic and primitives detection is easier. Indeed, we have directly facades hypotheses and planar

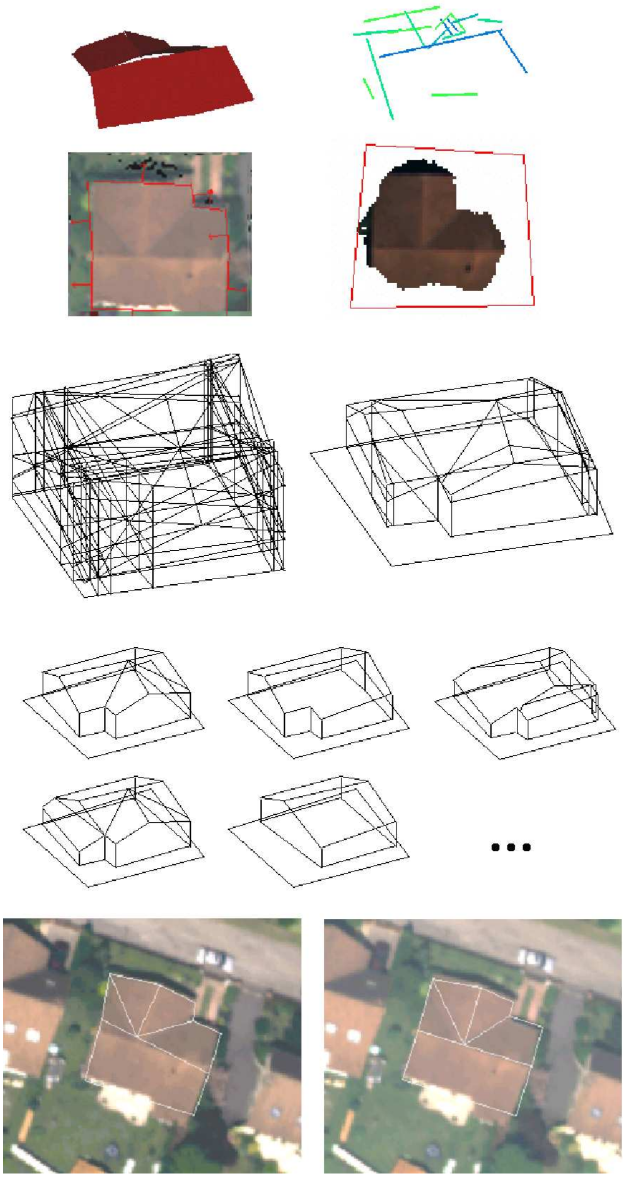

Figure 1: Each step of the algorithm applied to an example. 1st level : primitives detection (non vertical planes, 3D segments, facades, over-ground mask) ; 2nd level : resulting 3D graph before and after simplifications ; 3rd level : enumeration of possible solutions ; 4th level : superposition of the model chosen on a true orthophoto, before and after constraints application.

primitives detection can be restricted to some directions orthogonal to principal directions given by the building outlines. As the number of primitives is therefore reduced, we do not have any combinatory problems for the maximal cliques enumeration. In the following, we present two techniques for planes extraction using cadastral outlines, the first one using strong constraints, the second one relaxing these constraints.

2.2.1 Planes simulation The objective of planes simulation is to introduce strong constraints on planar primitives in order to improve robustness. This method is described in details in (Taillandier, 2005). From the cadastral maps, non vertical planes are inferred with the following rules :

- From each segment of the cadastral outline a gutter segment of z_g m is deduced. Initially, z_g is arbitrarily fixed at 0m.
- One plane is extracted for each gutter segment, orthogonally to this segment.
- All planar primitives have a given slope p initially fixed at 45˚.

From these plane primitives, we can then enumerate every possible reconstructions with the maximal cliques enumeration technique recalled in part 2.1. Some models are not however likely to represent building roofs (figure 2). A pruning step is thus necessary, in order to make the search for solutions more reliable. We constrain each facet to pose on the segment that has generated it, we impose a minimum angle between two edges (10˚) and a minimum surface of the facets (1 m^2).

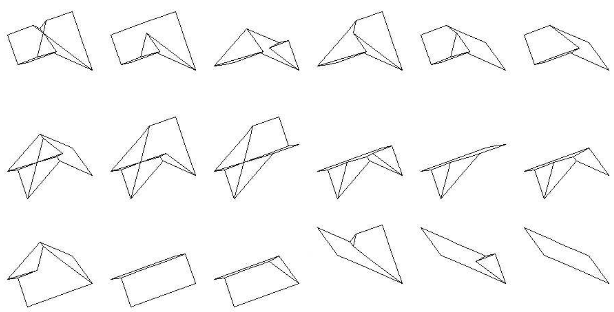

Figure 2: 18 possible solutions on a total of 83

The resulting models are enough simple to consider them equiprobable (figure 3) and discard the complexity term in the choice process. The solution is then chosen only on a criterion of adequacy to the data. In our case, since we initially fixed arbitrary altitude of gutter and slope, we use centered correlation on DEM (figure 4) as adequacy term to be independent of these arbitrary values.

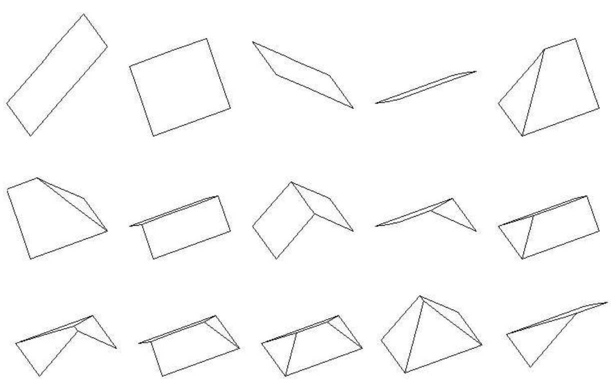

Figure 3: The 15 remaining solutions after simplifications

The last step consists in estimating altitude of gutter and slope of the planes. They are computed by minimization on the correlation DEM. A point M on a plane generated by a segment of gutter S and at the distance D_M from S is at the altitude z_M :

$$z_M = z_G + p \cdot D_M \tag{3}$$

where z_G is the altitude of gutter, p the slope of planes and D_M the orthogonal distance from the point P to the segment S. We minimize with L1 norm the difference between this model and the correlation DEM. This norm has been chosen because of its robustness : it is useful to overcome errors of correlation in the DEM and the non modeled superstructures of the roof.

Results obtained with this method are very good : 85% of the reconstructions are acceptable (see part 3.3). The real time constraint is also respected : in the very large majority of the cases, a result is obtained in less than 1 second.

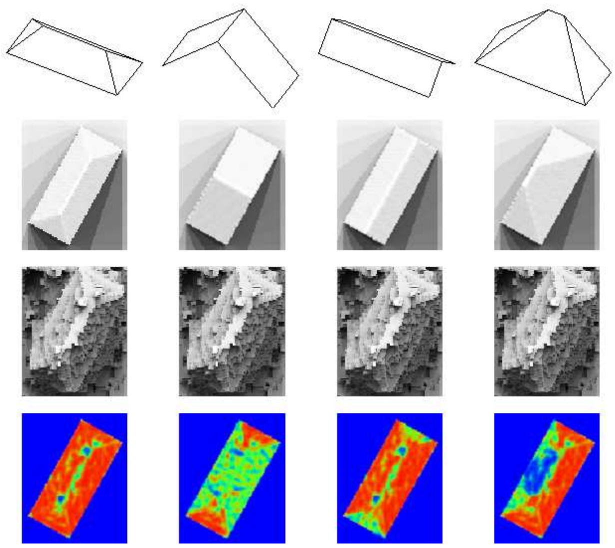

Figure 4: We calculate an altitude map corresponding to each model (2^{nd} row) that is compared with the reference DEM (3^{rd} row). The last row is the result of centered correlation between the 2 images (red : high correlation scores ; blue : low correlation scores)

2.2.2 Direct extraction of planes In the method previously described, constraints are very strong : there is only one slope of roof and one height of gutter per building. The objective of this second technique is to relax contraints in order to try to obtain more generality while maintaining a high level of robustness and then have more realistic reconstructions on buildings with irregular forms. In this case, to extract planes, we now exploit cadastral limits and DEM.

Cadastral limits utilisation Outlines of the buildings allow us to limit planes extraction. Indeed, most of the gutter being horizontal, we impose to a plane extracted from a gutter G that the horizontal component of its normal vector is perpendicular to G (figure 5). This implies that only 2 3D points and one 2D direction allow to define a plane. The first step of our approach is therefore to extract these particular directions from the outline of the building. The use of principal directions rather than the original segments from the outline allows for example to impose constraints of symmetry on the planes.

These principal directions allow to restrain the space of search of the planes in the DEM. The strategy used for extracting planes in the DEM is the robust algorithm of RANSAC.

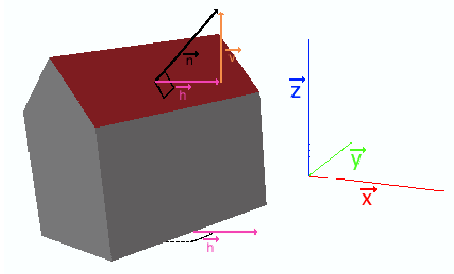

Figure 5: The horizontal component of a normale to a plane is perpendicular to the segment that generated this plane

RANSAC algorithm The principle of RANSAC algorithm (Fischler and Bolles, 1981) is to estimate parameters with the minimum necessary observations. These observations are selected randomly among the set of observations and we count the number of observations compatible with the model deduced. These steps are reiterated and the model chosen is the one that maximizes the consensus.
Two parameters have to be estimated : the error tolerance to determine whether or not an observation is compatible with a model and the number of tests to realize. The number of tests to realize k is (see (Fischler and Bolles, 1981)) :

$$k = \frac{\log(1-p)}{\log(1-w^m)} \tag{4}$$

where p is the probability that at least one subset of observations is correct, m is the number of necessary observations to estimate the model and w the probability that any observation is compatible with the model.
In our particular case, we want a plane equation and the set of observations is the 3D points of the DEM included in the cadastral parcel. We fix p at 99% and w is $\frac{n}{N}$, where n is the minimal number of observations to insure a plane presence (therefore n is linked to a minimal surface of planes that we want to detect) and N is the total number of points to consider. The other parameter is the error tolerance, in our case, it is linked with the intrinsic quality of the DEM used : σ_z. As we know the ratio $\frac{B}{H}$ of the aerial images that have been used to compute the DEM, and the resolution of these images, we can deduce σ_z :

$$\sigma_z = \frac{\text{resolution}}{B/H} \tag{5}$$

In our case, we do not want to find only one model, but several planes. Therefore we apply a few times this algorithm and remove at each iteration the points that are compatible with the plane detected. We stop the processus when there are not enough points remaining (less than 5% of the total of points). We explicitely introduce the knowledge of the principal directions so as to constraint the normal vector of the planes to extract but also to reduce the number of attempts. Indeed, in formula 4, m is the number of observations to define a plane. In general case, $m = 3$ (3 points define a plane), but since we have this additional data, $m = 2$. Therefore, we will randomly choose k couple of observations for each principal direction and finally choose the planes that maximize the set of consensus. For instance, for the building in figure 6 (6387 points of the DEM are inside the parcel and it is 27m large), the number of attempts is near 22 millions. With the pincipal directions, this number reduces to 260000 (130000 per direction). The phase of tests is critical for the complexity of our algorithm. So as to reduce it again, we make a realistic hypothesis : we suppose that each plane is in contact with a gutter. This will allow us to choose each couple of observations near a gutter segment (and inside the cadastral parcel). This method seems less precise, but we overcome this drawback by taking into account all points inside the cadastral outline to compute the set of consensus. For the same example, if the attempts are made in a 2m large belt around each segment, the number of attempts is reduced to 6200.

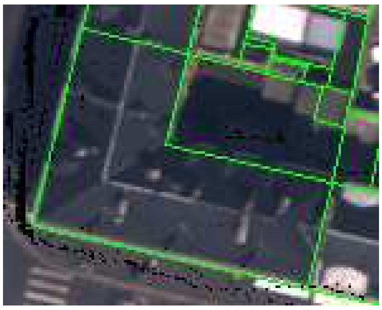

Figure 6: Example of a building

Choice of the best model After planes extraction, the 3D graph is built and the possible models are then enumerated according to the general algorithm. In order to choose the best model, we use the bayesian formulation described in part 2.1. Indeed, we have in general more models than with the method using simulated planes, it is then essential to reintroduce the complexity term. The adequacy to the data term is only computed in relation to the reference DEM. For each facet f of a model, we compute a score with the formula 6 :

$$\text{score} = \frac{\text{surf}(f)}{\underset{P\in f}{\text{card}}(P)} \cdot \frac{1}{\sigma_z} \sum_{P\in f} |\text{DEM}_{\text{ref}}(P) - \text{DEM}_f(P)| \tag{6}$$

where $\text{surf}(f)$ is the surface of the projected of the facet f in 2D, $\underset{P\in f}{\text{card}}(P)$ is the number of points of the DEM that belong to the facet f, $\text{DEM}_{\text{ref}}(P)$ is the altitude of the point P in the original correlation DEM and $\text{DEM}_f(P)$ is altitude of the point P projected vertically on the facet f. The score of a model is the sum of the score for each facet. Eventually, to link this quantity to equation 1 :

$$\sum_{f\in M} \text{score}(f) = -\ln(P(D/M)) \tag{7}$$

hence (see equation 1) :

$$\widehat{M} = \underset{M\in\Gamma}{\arg\min} \left\{ \sum_{f\in M} \text{score}(f) + \frac{\mathcal{L}(M)}{\beta} \right\} \tag{8}$$

We can adjust the adequacy term and the complexity term with the parameter β.

Results After all these adaptations, 89% of the reconstructions are acceptable (part 3.3). However, a few seconds are necessary for planes extraction. For instance, for the building on figure 6, the result is given in 4 seconds.

3 METHODS EVALUATION

3.1 Data

The evaluation was performed on 620 buildings of the urban center of Amiens (France). We have a correlation DEM of 25cm resolution (Pierrot-Deseilligny and Paparoditis, 2006) and the cadastral maps, preliminarily corrected so that each parcel corresponds to a building.

3.2 Some results

We present here some results (figure 7 and figure 8) and differences that can appear between the methods exposed.

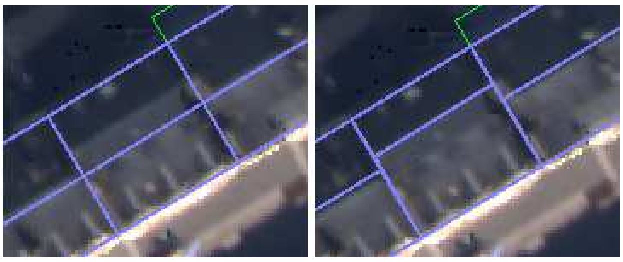

Figure 7: Comparison of the methods in the particular case of an asymmetrical building. The solution given by the method using simulated planes represents a symmetrical roof (on the left), the one given by the method using RANSAC planes extracted can represent this asymmetrical case.

Figure 8: Results obtained by the method using the first technique on a part of the urban center of Amiens

3.3 Visual evaluation

We want here to determine for each reconstruction "up to what point it corresponds to reality" ; only topological structure is observed. In this test, we do not take into account geometrical precision of the reconstructions. Each reconstruction of the evaluated area has been classified in one of these categories :

- *correct :* the reconstruction is in conformity with reality (we still tolerate oversights like fanlights and chimneys).
- *generalized :* the reconstruction is an acceptable caricature of the reality. We fix a limit that is the maximal size of details that can be forgotten (level of generalization of 1,5m).
- *surgeneralized :* it deals with reconstruction that could have been classified in the category "generalized" for a superior level of generalization.
- *false :* the reconstruction cannot be accepted, whatever the level of generalization chosen.

We present a synthesis of the results on the 620 buildings studied (table 1). The column "simulation" sums up the results obtained using simulated planes. The columns "β = 1000", "β = 500", "β = 100" synthesize the results obtained with RANSAC extracted planes and with different values for the parameter β. The best value for the parameter β, in term of rate of acceptable reconstructions (correct and generalized) among the three values tested is β = 500.

	Simulation	β = 1000	β = 500	β = 100
correct	76.61%	73.71%	73.23%	61.61%
generalized	9.71%	13.71%	16.13 %	25.48%
surgen.	0.16%	3.06%	6.55%	5.97%
false	14.03%	8.87%	6.77%	6.29%
failure	0.48%	0.65%	0.32%	0.65%
Total	100%	100%	100%	100%

Table 1: Results of the evaluation expressed as percentages

The rate of acceptable reconstructions using simulated planes is over 85%. Using RANSAC extracted planes and the parameter β = 500, the rate of acceptable reconstructions is 89%. However, we can notice that in term of exact reconstructions, the method using simulated planes is more effective.

It is interesting to cross the results of these two methods to know if a false reconstruction with one method is correct with the other one (table 2). For RANSAC extracted planes, we consider the parameter β = 500, the one that gives the best results.

We can read in table 2 that for 91 non acceptable reconstructions with simulated planes, 66 are acceptable with the other method (75%). We can then hope by stringing both methods together to correctly reconstruct more than 95% of the buildings.

	correct	gener.	surgen.	false/fail.	Total
correct	397	2	1	54	454
gener.	47	42	0	11	100
surgen.	12	5	0	5	22
false/fail.	19	5	0	20	44
Total	475	54	1	90	620

Table 2: The results for RANSAC extracted planes are in lines, crossed with results obtained with simulated planes in colomns. For instance, 54 false reconstructions with simulated planes are correct with RANSAC extracted planes

4 CONCLUSION AND PERSPECTIVES

4.1 Conclusion

We have presented in this article two methods producing automatically 3D models of buildings. The method using simulated planes gives acceptable results in 85% of the cases. The method using RANSAC planes extracted gives acceptable results in 89% of the cases. In the case of planes simulation, the execution is real time (less than 1 second) whereas a few seconds are necessary in the case of RANSAC planes extraction.

4.2 Perspectives

Three developments are envisaged. To be operational in a context with data of lower resolution (50-70cm), it can be useful that an operator can lead the algorithm to choose a general form of the solution. For example the operator could impose that the final reconstruction has a saddleback roof or a hip-roof. This is only valid for the method using simulated planes.
Then we will carry on the relaxation of contraints and introduce internal facades of buildings, this extension being possible in the original general algorithm.
At last, we will implement an alert system. Indeed, in order to make the process even faster, we can consider that in a massive production context of 3D database, an operator launches the reconstruction algorithm using simulated planes on a large area and only verifies the buildings whose reconstruction have given an alert by the system. For these buildings, either he confirms the reconstruction or he lauches the method using RANSAC planes extracted. By this way, we could hope to semi-automatically reconstruct 95% of the buildings.

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