A Top Down Strategy for Simple Crossroads Automatic Extraction

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ABSTRACT

The French National Geographic Institute (IGN) is working on problems related to the photogrammetric data capture automation. Based on our experience around the road network automatic extraction and on our cartographic requirements, we consider that crossroads detection cannot be simplified to a road hypothesis grouping problem. The inability for actual system to satisfy the cartographer and the necessity to focus our attention on crossroads areas impose the introduction of external data. A basic representation of simple crossroads drives the objects detection and set up a precise crossroads model in an image analysis system. The respect of the geometric accuracy, topology and object shape will build up our interpretation strategy. Intermediate results will demonstrate the interest of our specific modelization and the limit of the actual system. The efficiency of the strategy is discussed to propose solutions to the different identified problems.

RÉSUMÉ

L'Institut Géographique National (IGN) travaille sur les problèmes liés à l'automatisation des chaînes de saisie photogrammétrique. Forts de notre experience dans les systèmes d'extraction automatique du réseau routier et de nos exigences cartographiques, nous considérons qu'il n'est pas possible de simplifier l'extraction des carrefours routier à une simple interpolation entre différentes hypothèses de routes. On a mis en évidence l'incapacité des sytèmes actuels à satisfaire le cartographe et on demontrera le besoin de focaliser notre attention sur les carrefours. Un modèle adapté aux carrefours simple guide dans un système d'analyse d'image la detection des objets et instancie un modèle précis de carrefour. Le respect de la précision géométrique, de la topologie et de la forme de l'objet vont constituer les bases de notre stratégie d'interprétation. Des résultats intermédiaires demontreront l'intérêt d'une modélisation spécifique et mettront en évidence les limites actuelles de notre système. L'efficacité de notre approche sera ensuite discutée pour proposer quelques amélioration indispensables.

1 INTRODUCTION

IGN is creating a new topographic database and looks for methods to reduce operator's control and to accelerate the photogrammetric stereoplotting. The content corresponds to 1:25 000 maps with a metric accuracy in the 3 dimensions and its acquisition is based on stereoplotting of 1:30 000 aerial images (a 0.5 m of resolution) . The analysis of aerial images requires a complex reasoning, connected to the inherent complexity of images and man made objects (roads, crossroads, buildings). The figure 1 illustrates the required accuracy and the cartographic final representation. These three extractions are topologically correct and the geometric accuracy should satisfy a cartographer but the user interpretation is totally different.

According to the state of the art in crossroads detection, most of existing methods first focus on road extraction to create the road network. The detection of crossroads is often realized by perceptual grouping of road hypotheses. On that account, their local behaviour depends on road geometric quality and a small planimetric mistake can introduce a large modification of crossroads shape in cartography. [Groch, 1982] and [Heipke et al., 1995] use a road following method and detect crossroads when the road width changes. This method is sensitive to short edge interruptions. [Ruskoné, 1996] proposed a method

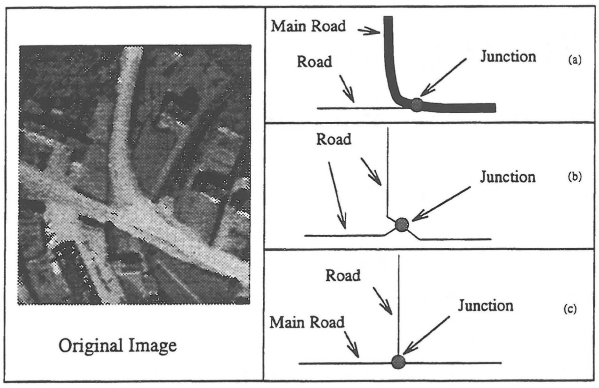

Figure 1: Different crossroads interpretation:
(a) cartographer (b)-(c) classical road detection

based on correlation of concentric radiometric profiles and [Guérin, 1996] based his approach on the road surface homogeneity. The different conclusions of these works established that the road network extraction quality could be improved in the crossroads areas.

Road and crossroads properties

Roads and crossroads are constructed with precise specifications to answer to a security problem and respect of the highway code. The main goal of a crossroads is to authorize some car exchange between different roads and to regulate the traffic. These properties allowed us to consider a limited list of possible crossroads. This list is composed by different kind of roads (highways,urban roads, small rural roads, national...), by the possible crossing (two highways, two rural road...) and by impossible crossing (a rural road and an highway). In order to limit our investigation field, we do not consider simple junctions of rural road crossing rural road. This at the moment simplification is necessary to study the cartographer requirement and the specific image processing problems due to the crossroads complexity. These problems are not considered actually in full or semi automatic road network extraction systems. The multiplicity of applications and the images diversity (satellite or aerial) explain the few works on this subject. However, some are considering cartographic road specifications as [Bordes, 1997]. They proposed a simple crossroads model and concluded to their incapacity to satisfy the cartographic accuracy.

A Main road idea

The lack of these methods is partly due for simple crossroads to non consideration of Main Road concept (figure 1). This Main Road idea depends on of the local geometry and global semantic information. It is fundamental for the operator's interpretation and guides his reasoning for representing explicitly and clearly the crossroads. Reasoning is based on the car flow driving on this road which influences the width and global rectilinearity of roads. The flow defines the road width and enforce the choice of road markings or physical structure. This reasoning is also based on the car traffic which is an explanation to the traffic circle or red light in crossroads. We consider these complexe junction (traffic circle, intersection on highways) as elementary "sub-junction" separated by a Main Road and subdivided in few simple crossroads. The hierachical description of complex crossroads is another element to demonstrate the necessity to study simple crossroads.

The image complexity

The main road concept is an interesting idea to guide the image interpretation. This interpretation is still difficult to automate and specially in aerial images. The high resolution introduces a lot of contextual information which is very hard to consider in a simple crossroads model. The existing relations between different objects detected in the image could increase confidence in our detection. Some context relations like cars-road in [Ruskoné et al., 1996], river-road or railway-road in [Bordes et al., 1995] might reduce the false detection and improve the final quality of the restitution. But there is no systematism and these kinds of information are necessary when simple methods fail. The use of contextual knowledge for the road extraction from aerial images has not yet received our attention. We consider that it is more efficient to incorporate our external data to focus our attention on specific areas and to guide the detection. [Guérin, 1996], [Bordes, 1997] or [DeGunst, 1996] improve aerial image interpretation by incorporation of knowledge source (road maps, Cartographic DataBase, human interaction, Digital Elevation Model...).

To summarize our studying context, we are going to consider all simple crossroads in rural context. This limitation should make it possible to demonstrate the specific cartographic problems. We will also take into account a rectilinear road model and consider a main road concept to constrain the interpretation and to axe firstly our road detection on the "easiest roads". External data will be used to focus our attention on interesting areas and drive our image interpretation with a Top Down strategy. Besides, we consider only the roads proposed by external data, we do not look for other roads or other crossroads. We explain in this paper the necessity to create a basic and a precise model for simple crossroads. We will develop precisely the Top Down strategy, the feedback (refocusing), and some specific processing. Intermediate results will demonstrate the interest of this method and the limit of the present version. Finally, the efficiency of the strategy is discussed to propose solutions to the different identified problems.

2 A SIMPLE CROSSROADS MODEL

The external database is obviously far less accurate than the image to be processed and will be used to draw up this basic crossroads model. In the field of high resolution imagery, many details complicate the detection and external data provide geometric and semantic information about the object of the scene (roads for example). This basic model will guide the system to built up a precise model through image analysis. This precise model is representing the image reality.

2.1 A basic model

It is necessary to adapt the external data (map, cartographic database...) to the application and create a specific crossroads model. The geometric information is used to focus attention on interesting area (crossroads and roads for example), to propose a rougher geometric description of the object than the imagery (number of road arriving in the crossroads, main direction of these roads) . This geometric information is also used to drive the detection. The external data contain some semantic information about the road width, the number of ways, the kind of road (highway, secondary road, principal road...). These informations are combined to the geometric information to propose a Main Road hypothesss *Axis_DB* which is divided in three classes:
- Secondary: geometric continuity
- Principal: semantic continuity
- Ultra-Principal: geometric and semantic continuity

The basic model organization is presented in the figure 2. A CrossRoads_DB is a node of our road network and can be connected to few Road_DB (1:N) and/or one Axis_DB (1:1).

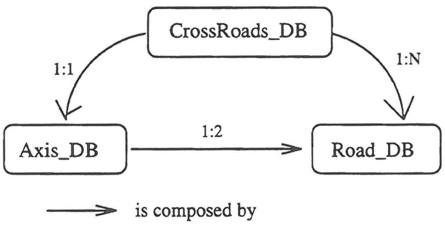

Figure 2: A basic model for simple crossroads

2.2 A precise model

A simple crossroads is only composed by roads without any traffic circle or complicated road paintings. Our hierarchical model (figure 3) represents the structure of many crossroads. The crossroads is described by a node (a point), a list of connected roads called *Road_Im* and sometimes a Main Road called *Axis_Im*. This road model is defined by two basic criteria: geometric and radiometric.

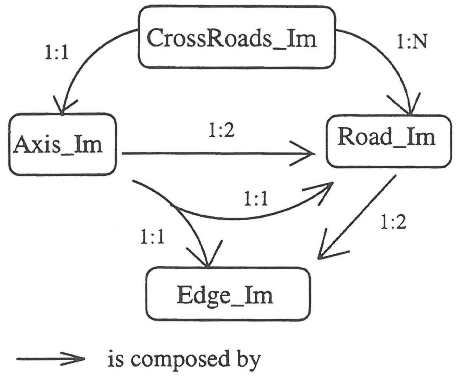

Figure 3: A precise crossroads model

- the geometry is particular in our images because we focus our attention on a local part of the road. In that way, a road is a rectilinear object crossing our image. A road is represented as a ribon with 2 parallel road *edge_Im*
- the radiometric characteristics depend on the road surface material, the texture (homogeneity), the lighting, the contrast between this surface and the close environement.

In many systems, a road is considered as a long ribon. The global constant curvature authorize us to approximate a part of it as a straight ribon. An *Edge_Im* has to answer to this rectilinearity constraint. This choice should demonstrate the inability of the system to detect correctly non linear or a fragmented edges. This limitation is a first approach necessary to detect the easiest roads or the main edge directions in an image. The ribon imposes a parallelism constraint and an *Axis_Im* is created by a geometrical grouping or by reasoning with high level knowledge. The geometric similarity is due to a global conservation of the road width and to the sweet curvature. The radiometric characteristics of roads are considered in many road network systems. The road surface is often bright and homogeneous compared to its close environment. We notify that road edges are often contrasted but the gradient direction of the edge is a more stable information in our aerial images. The antiparalllism is due to an inverse orientation of the egdes gradient. [McKeown and Denlinger, 1988] consider also that the"road profile varies very gradually" along the track of the road. This information can be used to consider a global image similarity (homogeneity, radiometry) between the two dedicated *Road_Im*.

3 THE INTERPRETATION STRATEGY

The general idea of our interpretation strategy is to use *a priori* knowledge to guide the crossroads extraction in the image. The goal of this system is to complete the basic model created with the external data through image analysis and to construct the precise crossroads model compatible with the cartographic specifications. A rule based system analyses each

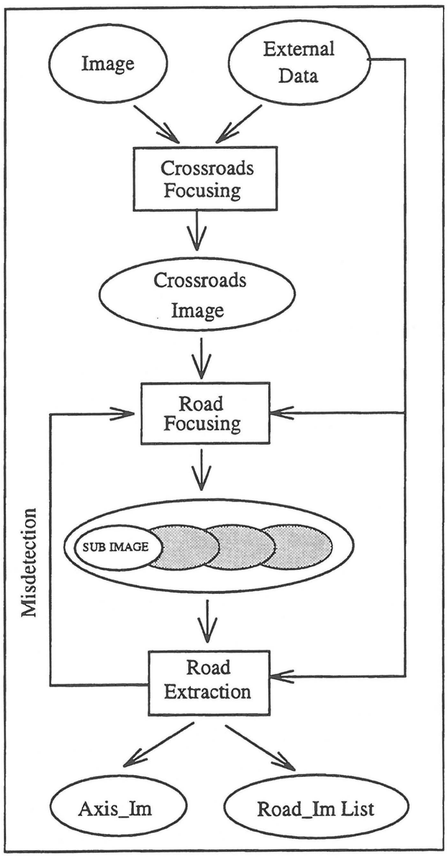

Figure 4: The complete system organisation

crossroads identified by the external data to set some of the model components. Rules modelize the external data information and the knowledge used by an expert to draw up a crossroads description. These rules transform the imprecise to fuzzy information, make reasoning on local road orientation to propose possible crossroads shape and consider the global linearity of the road (between two crossroads) to estimate the local optimal direction.
These geometric and semantic informations are used to focus and drive the detection on the easiest road at first. This part of the image interpretation strategy is based on a Top-Down strategy. The integration of the basic model knowledge is necessary to extract the *Crossroads_image* centered on the approximate *CrossRoads_DB* position. This knowledge is used to focus attention on extracted road images (*Sub_Images*) in the optimal direction. The existence of *Axis_DB* informations will obliged the system to detect firstly an *Axis_Im* in the image.

4 A LOCAL ROAD EXTRACTION

The basic model (paragraph 2.1) contains for each road hypothesis some semantic informations (width and width tolerance, *Axis_DB* or *Road_DB* directions, *Crossroads_DB* position). The **Road Extraction** module in figure 5 uses a list of independant or grouped *Sub_Images* and gives out an *Axis_Im* and/or a list of *Road_Im*. The **Edge Detection** is composed by a classical [Deriche, 1987] gradient function ($\alpha = 1$), a function for the local maximum detection and an Hysteresis to filter the noise ($Th\_Low = 10$ and $Th\_High = 15$). Our problem is about the edges post processing and we consider that any edge detection process could be used for this problem.

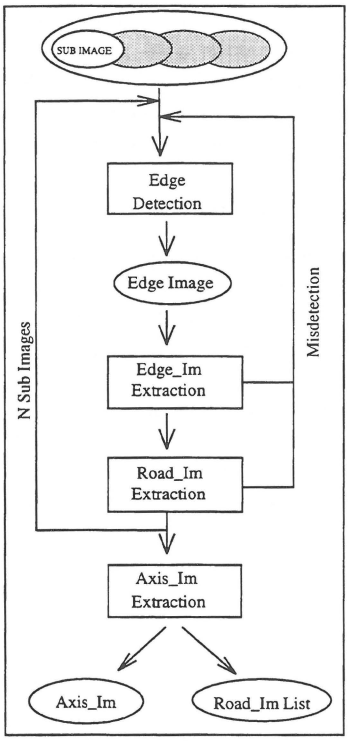

Figure 5: The Road Extraction Module

4.1 The *Edge_Im* Extraction

The goal of this process is to detect in an *Edge Image* the rectilinear egdes. Many solutions exist to detect the possible road edges. [DeGunst, 1996], [Bordes, 1997] and [Baumgartner et al., 1997] have done a review of the existing methods for the last 10 years in automatic or semi-automatic road local extraction. Our strategy requires a local estimation of road edge hypothesis. The rectilinearity of our model reminds us to the **Hough Transform** in straight line space. The accumulation of edge points should create in the Hough space, a pinpoint accumulation. The **Quantification** process will extract the best *Edge_Im* candidate. The **Validation** filters the false detections and evaluates the quality of the probable *Edge_Im* hypothesis.

4.1.1 A Hough Transform Algorithm

- **State of the art:** This method was proposed by [Hough, 1962] but [Rosenfeld, 1969] and [Duda and Hart, 1972] applied it to line detection in pictures. The number of scientific publications on the Hough Transform is huge: from the simple line detection to the complex curve extraction. [Maître, 1985] and [Illingworth and Kittler, 1988] present a complete review on Hough Transform (HT). Our application requires a robust straight line detector and the efficiency of the HT in the line space has been now established.

- **Theory and algorithm:** We are accumulating every edge points of the image. We use the gradient direction and the point position to define the Hough coordinate (ρ, θ) with the relation:

$$\rho = x\cos\theta + y\sin\theta \tag{1}$$

$$\theta = F(\theta_G) \tag{2}$$

$$\theta_G = \arctan(\frac{Gy}{Gx}) \tag{3}$$

where $\vec{G}(G_x, G_y)$ is the gradient. The reference is the image center to limit the side effects. We are accumulating the gradient direction and the elementary accumulation is weighted by the effectiv length of the hypothesis in the image. Each accumulation in the Hough space is a straight line which crosses the image and generates a *Bord_Im* . The figure 6

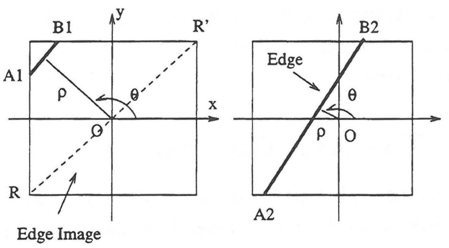

Figure 6: Accumulation element computation

represents different possible edge hypothesis generated by the edge image point and its Gradient direction. If the segment $[A_1B_1]$ or $[A_2B_2]$ is our edge and $[RR']$ the longest hypothesis, then the confidence in our point can be measured with the fraction of these two length. This confidence is our accumulation element (Accu) and we consider that the $[A_2B_2]$ is more accurate than $[A_1B_1]$. Finally, the Hough accumulation element computation is:

$$Accu_1 = \frac{[A_1B_1]}{[RR']} \qquad Accu_2 = \frac{[A_2B_2]}{[RR']} \tag{4}$$

- **Correction of bias:** we consider in our accumulation array an elementary cell (1 pixel by 1 degree). Different errors are introduced during the accumulation and will smooth the Hough peak. Errors are due to the accuracy of edge localisation and to the gradient orientation. We estimate for $\alpha = 1$ the edge

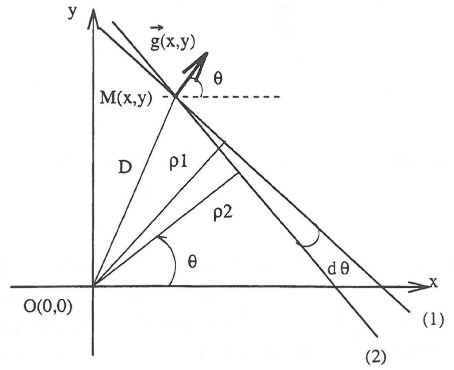

Figure 7: Relation between $\Delta\rho = \rho2 - \rho1$ and $\Delta\theta$

orientation gradient accuracy $(\Delta\theta)$ around 3 degrees. The relation between $\Delta\rho$ and $\Delta\theta$ is:

$$\Delta\rho = \rho\left(\frac{1}{\cos\Delta\theta} - 1\right) + \\ + \left(\sqrt{D^2 - \rho^2} - \rho\frac{\sin\Delta\theta}{\cos\Delta\theta}\right)\sin\Delta\theta \tag{5}$$

where $D = \sqrt{x^2 + y^2}$ on figure 7. This relation express the fuzziness of the image side limits. A circular image will avoid this error but destroy usefull informations in a situation of misdetection. We estimate the localisation error in an image 100x100 for a $\Delta\theta = 3$ degree then $0 \leq \Delta\rho \leq 3$ pixels. We know that our cell dimension is not representative of the effectiv accuracy. A final smooth is necessary to correct the edges orientation uncertitude with a 3 pixels x 5 degrees average. This manipulation is necessary to limit false detections. We present an example in

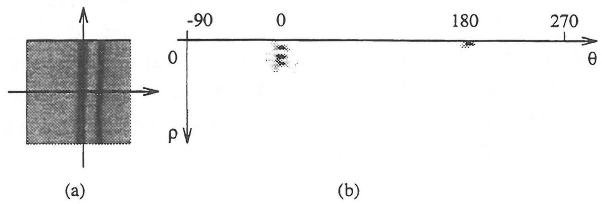

Figure 8: Example: (a)The original *Sub_Image*
(b) The Hough accumulation image

the figure8. The original image is interesting because there are different parallels *Edge_im*. The position of the the left *Edge_Im* is at the left of the Hough origin and in this situation $\theta \simeq 180$ The other *Edge_Im* are localised at the right of this origin and $\theta \simeq 0$.

4.1.2 The Space Quantification method

We consider still a Top Down strategy which motivate us to use a simple function for the peak detection. Our application should create particular Hough

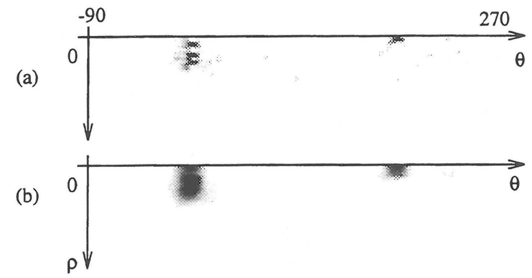

Figure 9: (a) The Hough accumulation image
(b) with a 15x15 average

signature with a minimum of two peaks (figure 'ref-Houghcomp(a). These peaks should be distant of the minimum road width ($\simeq$ 5 pixels). These two peaks are rectilinear hypotheses and should be parallel. We limit the parallelism to a 3 degrees error (estimation of the edge orientation accuracy). Considering this, a multi-average method followed by a local maximum detection should be efficient. A primary 10x10 average and a 15x15 filter localize the major peaks (figure 9(b)). A fine detection (3x3 filtering) is following to detect precisely the peak coordinates.

4.1.3 Failure and decision

We observed different problematic situations due to an approximativ focusing. First of all, if the space quantification inform us that no solution were detected, it means that we have to refocus our attention on another area. The initialisation of the new area is calculated considering the other *sub_images*. Finally, if one road is missisng in our crossroads, it is possible to create a new interpolate junction. The direction will reprocessed and a new *sub_image* will be resampled.
Second of all, if the space quantification inform us that one solution were detected, it means that one edge is hide (tree, shadows), not contrasted at all or is out of the area. In the last case, we should observe non central position which inform us the refocusing direction. In the others case, a high level reasoning might complete the solution.

4.2 The Road Extraction

4.2.1 A simple grouping method

A *Road_Im* hypothesis is created with two independant and parallel *Edge_Im* primitives. The geometric characteristics of two parallel hypotheses are:

- width conservation
- no possible crosspoint
- (2 m < road < 20 m)
- (-45 degree<Limit of Road Direction<+45 degres)

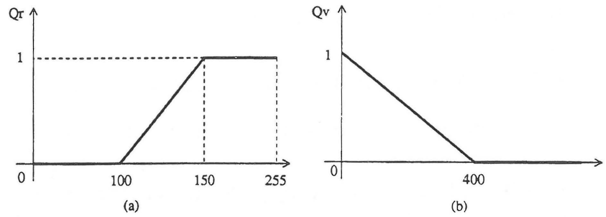

Figure 10: The *Road_Im* fuzzy quality function:
(a) Radiometry (b) Variance

4.2.2 The Quality Evaluation

The quality is calculated with fuzzy function (figure 10). These quality are fusionned with a MIN(Q_R,Q_v) operator. The average of the radiometry is computed under the axis hypothesis as the variance to this average. These informations are representativ of a classical road model which consider a road as a homogenous surface often brighter than his close environment. We introduce also the orientation of the Gradient to advantage the anti-parallel pairs. It means that two parallel edges have an opposite gradient orientation. But this quality is also depending on each *Edge_Im* confidence measure.

4.2.3 Misdetection and decision

A failure can be the consequence of the non respect of parallelism (geometry). If this misdetection is due to the non rectilinear road form, then it necessary to change the image processing and try to detect a more complex form (polygonal, circular...). But if it is a radiometric failure, then we have to modify our fuzzy functions because the unhomogeneity of the road or the darkness of the surface are possible explanations.

4.3 The Axis Generation

Actually, this process is considering two *Road_Im* hypotheses and the external data. If the *Crossroads_DB* informs us about the possible existence of an axis, then we run the Axis Generation. To the contrary, the *Road_Im* hypotheses stay independant. This module considers the global axis geometric constraint which is caracterized by his global width continuity. A fuzzy function comput a quality measure with this width difference (figure 11(a)).

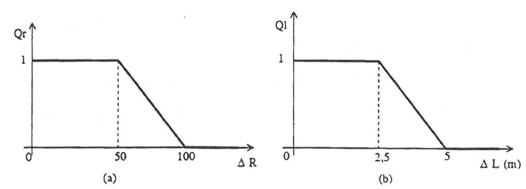

Figure 11: The *Axis_Im* fuzzy quality function:
(a) Radiometric Difference (b) Width Difference

Another fuzzy function is considering the radiometric continuity (figure 11(b)). These quality measures are connected to the *Road_im* hypotheses quality. We use a MAX(Q_1,Q_2) operator. This operator consider the best quality hypothesis as discriminating. Finally, we introduced the *Road_im* confidence to weight the final quality evaluation of our *Axis_Im* hypothesis.

5 RESULTS

The results presented in this article are not presenting the complete reconstruction of a crossroads. The system is at the moment focusing his attention on the interesting areas: the crossroads (figure 12) and the roads (figure 14). These focusing are considering informations proposed by the *CrossRoads_DB* model represented in white color in the figure 12. Each *Road_DB* direction is necessary to resample the differents *Sub_Images* (figure 13). The Road Detection propose a list of *Road_Im* hypothesis (figure 14). We represented in white color the best quality hypothesis and in black the possible hypothesis. The textit-CrossRoads_DB inform us a Main Road is connecting Road 2 and Road 4. We also notify in the Road 4 image the best quality solution is not the good one. The figure 15 demonstrate the ability for the system to correct this error and propose a *Axis_Im* centered on the road. The Road 1 an Road 2 hypothesis should be project on this *Axis_Im* but before, it is necessary to study the inner crossroads reality.

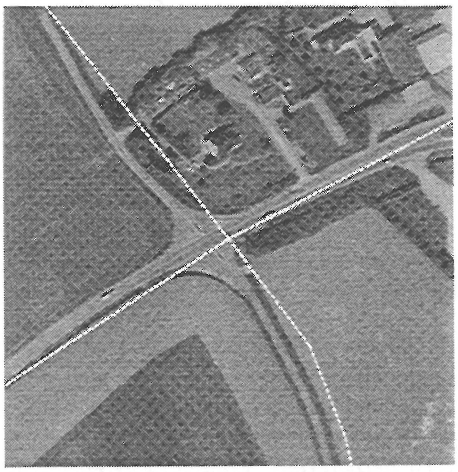

Figure 12: Initial image with the *Crossroads_DB*

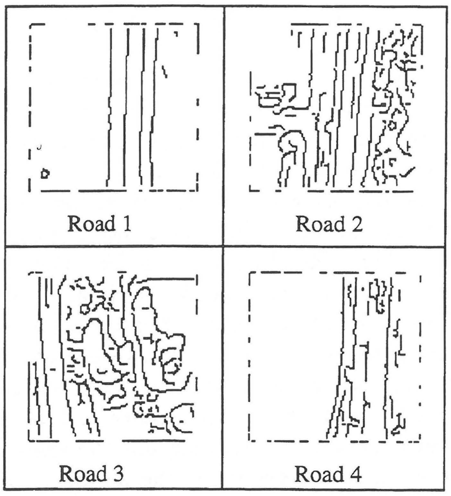

Figure 13: Our Edges for each *Sub_Images*

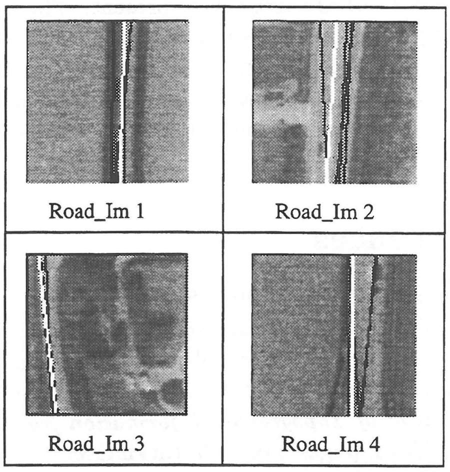

Figure 14: The different *Road_Im* possible solutions in white: the best solutions

Figure 15: The result of our *Axis_Im* creation

6 CONCLUSION

In this paper, we presented a crossroads modelling using a knowledge database. A basic crossroads model is derived from these external data and is necessary to focus our attention in the image. This basic crossroads drives the road detection and help to the reconstruction. The image interpretation is based on a Main Road idea and is Top Down in order to delay as much as possible the image prossessing. We presented a road detection process based on the Hough Transform algorithm and we evaluate the quality of our road hypothesis with fuzzy functions. We presented our intermediate results and the geometric road accuracy is satisfying but the exact position of the node is not known at the moment. This final reconstruction depends on the image reality in the crossroads center area where road paintings and physical separator are frequently present. The detection of other object in the center seems to be necessary to rebuilt the whole crossroads. Moreover, it is necessary to manage some particular situations to consider more possible failure and imagine an efficient validation process.

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