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Article

A Modular System for Road Updating, Refinement and Classification from Satellite Images

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Summary: The extraction, refinement and verification of intact and damaged infrastructure are important issues for the management of civil crises, e. g., caused by flooding or earthquakes. In this paper, the development of a system for the automated detection of roads, their geometric and semantic refinement as well as classification into different states of accessibility from multi-sensorial imagery is presented. The system is intended to supply information being required for the coordination of rescue teams and the implementation of emergency actions. It is the result of long-term research on different aspects of road extraction, which has been extended and adapted in the context of the bundle project DeSecure to build up a framework providing all relevant information regarding the extent and impact of crises scenarios within shortest timeframes. The results of classification system show the improvement of the fast interpretation of road networks after natural disasters using automatic approaches.

Zusammenfassung: *Ein modulares System zur Aktualisierung, geometrischen Verfeinerung und Klassifikation von Straßen mit Hilfe von Satellitenbildern*. Die Extraktion, geometrische Verfeinerung und Verifikation von intakten und beschädigten Infrastrukturobjekten sind wichtige Fragestellungen bei zivilen Krisen, wie zum Beispiel Überflutungen oder Erdbeben. In diesem Artikel wird die Entwicklung eines Systems beschrieben, das mit Hilfe von multi-sensoriellen und multi-temporalen Bildern eine automatische Detektion von Straßen, eine geometrische und semantische Verfeinerung und eine Klassifikation in verschiedene Zustände der Befahrbarkeit durchführt. Das Ziel des Systems ist die Bereitstellung von Informationen über Straßen, die für die Koordination von Hilfskräften von großer Bedeutung sind. Die präsentierten Ergebnisse basieren auf langfristiger Forschung im Bereich der Straßenextraktion, die im Rahmen des Bündelprojekts DeSecure angepasst und erweitert wurden. Das erweiterte System, bestehend aus den drei Modulen Straßenextraktion, Verfeinerung und Klassifikation liefert ein Rahmenwerk, um sämtliche relevante Informationen über Straßen in kürzester Zeit in Krisenfällen zur Verfügung zu stellen. Die Ergebnisse zeigen, dass mit Hilfe der automatischen Klassifikationsverfahren die benötigte Zeit zur Interpretation von beschädigten Straßen nach Naturkatastrophen erheblich reduziert werden kann.

1 Introduction

A significant increase of natural disasters such as flooding has been observed over the past decades. While it is not absolutely clear, whether the number of disasters has really grown or only appears so because of the advances in world-wide communication and global observation methods, there is no doubt that the disasters' impact on the population has dramatically increased due to the growth of population and material assets (Huadong 2009). The regrettable death of people is accompanied by heavy economic damage, which leads to a long-term backslide of the region hit by the disaster. This situation calls for the development of integral strategies for preparedness and prevention of hazards, fast reaction

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in case of disasters, as well as damage documentation, planning and rebuilding of infrastructure after disasters.

It is widely accepted in the scientific community that Remote Sensing can contribute significantly to all these components in different ways, especially because of the large coverage by remotely sensed imagery and its global availability. The bundle project DeSecure will build up a framework to provide all relevant information regarding the extent and impact of crises scenarios within shortest time-frames. Time, however, is the overall dominating factor once a disaster has hit a particular region. Several time consuming aspects exists: firstly, available satellites have to be selected and commanded immediately. Secondly, the acquired raw data has to be processed with specific signal processing algorithms to generate images suitable for interpretation. Thirdly, the interpretation of multi-sensorial images, extraction of geometrically precise and semantically correct information as well as the production of (digital) maps need to be conducted in shortest time-frames to support crises management groups.

While the first two aspects are strongly related to the optimization of communication processes and hardware capabilities (at least to a large extend), the main methodological bottleneck is posed by the third aspect: the fast, integrated, and geometrically and semantically correct interpretation of multi-sensorial images. Therefore the development of methods for automatic understanding and interpretation of airborne and space borne optical and radar images to support the fast reaction after disasters is needed. In the following, special focus is on the extraction, analysis and characterization of roads due to their importance for the immediate planning and implementation of emergency actions. Different types of models – physical, stochastic and semantic models – will therefore be used in an integrated approach.

2 Related Work

The extraction of roads from remotely sensed image data has been of considerable interest in recent years, mainly driven by the rapid progress of 2D and 3D geographic information systems as well as navigation systems and their increasing importance in daily life. The advances can be seen in the relevant computer vision literature, for instance in the compendia and overview papers of Grün et al. (1997), Mayer (1999), Baltsavias et al. (2001), Gamba et al. (2003), Gerke et al. (2004), and many others.

Fig. 1: IKONOS image from the Elbe flooding in Germany in 2002.

Despite of numerous technological advances the process of semantic data acquisition still needs lot of manual interaction of a human operator to yield results relevant for practical applications, which is of course both time-consuming and expensive. While this is true for optical images, the situation is even harder for Synthetic Aperture Radar (SAR). SAR is an active and coherent imaging technique which leads to the well-known speckle noise and image derogations due to radar shadow and layover. Thus, the imaged objects are subject to drastic changes in their appearance depending on the radar illumination parameters. Deterministic and stochastic modeling of this varying object appearance is far from being solved today. The scientific challenges of man-made object extraction, in particular roads and buildings, from SAR data can be viewed, for instance, in Baumgartner et al. (1999), Wiedemann & Hinz (1999), Wessel & Hinz (2004), Sörgel et al. (2006), Hedman et al. (2006).

However, besides the drawbacks due to the specific viewing geometry and coherent imaging, SAR holds also some prominent advantages over optical images, which are in particular helpful in crisis situations. For instance, SAR is an active system, which can operate during day and night. It is also nearly weather-independent and, moreover, during bad weather conditions SAR is the only operational system available today.

Hence, under the light of today's and tomorrow's available optical and SAR satellite systems, the development of integrated approaches for object extraction from multi-sensorial images are an attractive alternative to support fast and accurate information extraction. To this end, models and extraction strategies need to be developed that integrate the different geometric and radiometric sensor characteristics attached with stochastic models to accommodate for the inherent modeling and measurement uncertainties.

However, the sole extraction of roads can hardly fulfill the requirement which is needed in case of natural disasters. Using additional road networks from GIS-database can improve the reliability to draw conclusions about the functionality of a road network. Since the geometric accuracy of the road database is essential, methods for refinement are needed. Parametric active contours, often called snakes (Kass et al. 1988, Blake & Isard 1998) can be used for the improvement of the geometrical accuracy. In Butenuth & Heipke (2010) network snakes are applied to a road network. Network snakes have the crucial advantage to perserve the topology of networks. In this paper network snakes are investigeted concerning their performance in natural disaster scenarios. In Gerke et al. (2004), Gerke & Heipke (2008) a quality assessment of existing road data is presented using remotly sensed images. In case of natural disasters the assessment concerning the trafficability of roads is investigated in Frey & Butenuth (2009) for multsensor imagery. The improvement of the assessment using multi-temporal imagery is discussed in Frey & Butenuth (2010).

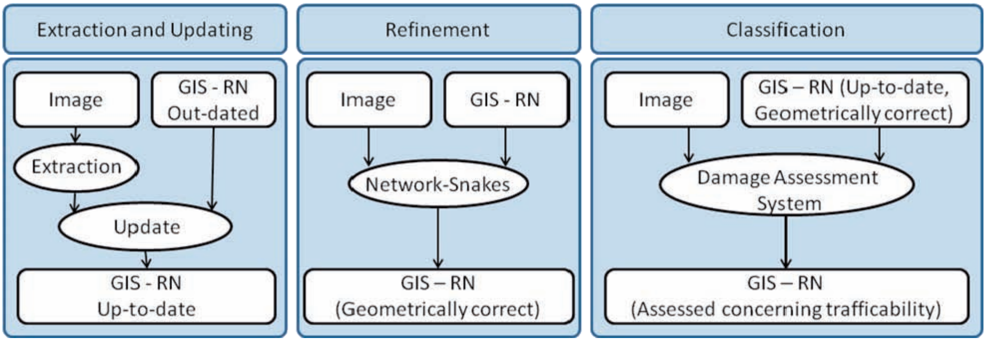

Fig. 2: The three moduls of the system (RN = road network).

3 System and Strategy

3.1 *System*

At the moment, fully automatic approaches for object extraction must still be regarded as a subject of fundamental research, and they seem not to be able to find their way into operational work flows in the very near future. On the contrary, semi-automatic approaches seem more likely to be useful in operational applications. Automatically achieved results nonetheless may provide a basis for efficient checking, editing and improving.

It is assumed in the following that road axes are already available as input data, which might stem from an automatic extraction or an existing road database. These road data, however, might be outdated, geometrically displaced and/or partially semantically wrong. Hence, the framework for the automated detection and classification of roads from multisensorial imagery is conceptually divided into three main parts. The first part comprises the user-assisted updating of roads. It comprises an automated internal evaluation of the input data providing measures about the reliability of road parts. In case of incomplete input data – e. g., of an automatic extraction – this can be used to guide an operator during editing and completing the results, for instance by interactive road tracing. The second part includes road refinement, which basically involves the application of a network snake approach to refine the road network in terms of geometric accuracy. Naturally, during this phase only centerlines of intact road segments can be refined, while those of damaged or flooded roads will usually not improved. Hence, conceptually, this module is only applied to roads which have been identified as "reliable" by the above internal evaluation. The third module, finally, is devoted to classify the whole road network into accessible and damaged/flooded road parts.

In the following, the individual modules (cf. Fig. 2) are described in more detail. However, the system still contains stand-alone modules, which are tested and evaluated only individually. Integrating them into a monolithic software system is not within the scope of this research work. The performance of the individual modules are exemplarily shown at an IKONOS image from the Elbe flooding 2002 (cf. Fig. 1)

3.2 *Road Internal Evaluating and Road Updating*

Existing GIS data nor the results of an automatic object extraction may not be expected to deliver absolutely perfect results and, thus, for meeting predefined application requirement, a human operator must inspect the automatically obtained results. In order to speed up the time- and cost-intensive inspection, the system should provide the operator with confidence values characterizing the system's performance – a so-called internal evaluation. This information can only be derived from redundancies within the underlying data or the incorporated object knowledge. In this context, "object knowledge" means knowledge that is purely described by the object model and not by other external data. The results of internal evaluation are particularly important

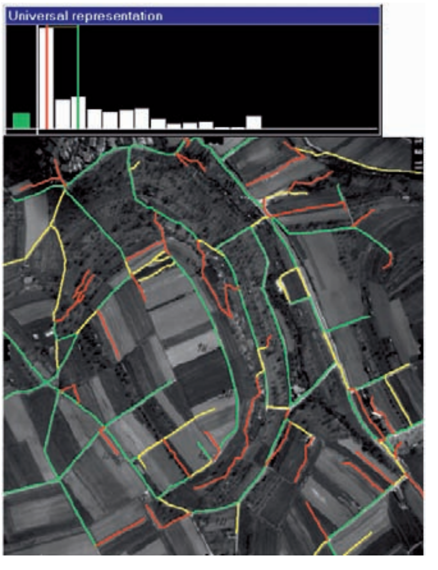

Fig. 3: Overview of self-diagnosis. Top: Length-weighted histogram of evaluation scores (left-most bar indicates mean value = green in this example), thin vertical lines indicate thresholds between categories. Bottom: Overview window.

if the extraction results are combined with other data, e. g., if they are fused with results from other extraction approaches or if they are used for the update of GIS data. On the other hand, they are also very useful for guiding a human operator during post-editing the results of an automatic extraction. In practice, however, this is rarely the case.

Object properties that relate to global characteristics of roads are used in this context. A road network, for instance, must be in accordance with some typical global network characteristics: few connected components, no clusters of junctions outside urban areas, convenient connections between various places depending on the terrain type etc. Such properties are used in Hinz & Wiedemann (2004) to evaluate the reliability of portions of the network with a fuzzy-set theoretic approach.

To allow a quick and effective inspection by a human operator, the evaluated road segments are displayed in an overview window and categorized into three classes: green (to be accepted), yellow (to be checked), and red (to be rejected). In addition, the average quality of the evaluated network and the distribution are displayed (cf. Fig. 3). Whenever a particular road section is sought to be inspected in more detail, it can be selected in a separate cutout to investigate the evaluation details (cf. Fig. 4). Based on the visualization and the quality information, the operator may decide how to handle a particular road section — whether it should be retained, deleted, or edited. Of course, setting the two thresholds between the categories is critical. However, as the test series in Hinz & Wiedemann (2004) show, deriving these thresholds from the statistics of the evaluation scores is a simple but surprisingly effective approach. In particular, in these examples the threshold between the yellow and the category is simply the minimum (zero score), while the threshold between the green and the yellow category is defined as the median of all evaluation scores (see, e. g., Fig. 3).

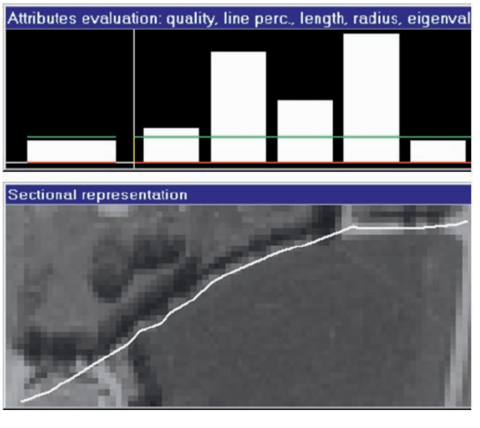

Fig. 4: Detailed inspection of evaluation results of a specific portion of the road network. Bars indicate results of evaluation for each criterion involved ([0 ; 1]).

To analyze the reliability of self-diagnosis, we matched the internally evaluated results to a manually plotted reference (see details and figures in Hinz & Wiedemann 2004). The comparison showed that almost every road section of the green category is a correctly extracted road (above 90%). The self-diagnosis also detects "false alarms" in the extraction with high reliability (80% – 90%). Considering the evaluation of yellow-labeled road sections one can state that these parts of the road network should indeed be investigated by a human operator because the correctness values are generally lower and vary to a notable extent (50% – 75%). It is furthermore interesting to observe what would happen if an operator had checked exclusively the yellow-labeled road sections. Under the assumption that a human operator is able to discern correct and wrong detections without any error, the correctness of the overall result would remain in the range of 95%, while the amount of editing drops down significantly: only 25% to 50% of the whole road network need to be checked.

However, it is important to note that one can improve only the correctness through employing this scheme for internal evaluation. Completeness can only be increased when identifying potential gaps in the extraction and closing them. To this end, the system provides user-assisted tools for road extraction. Semi-automatic, i. e., user-assisted, tools have the advantage that the quality of the results is guaranteed, because a human operator controls the data acquisition process and prevents errors on-line. Yet the overall benefit of such systems depends not only on their sophisticated algorithms but also on adequate tools for editing. Quite a lot of promising approaches for semi-automatic road extraction have been presented and analyzed in the last decades.

Road trackers and path optimizers are characterized by complementary properties: Road tracking is usually based on a road profile selected by a user for a particular road to be traced. In this way, the specific radiometry of this road is included into the procedure. This is in particular helpful when different roads of varying appearance should be extracted. Such appearance-based constraints are commonly not included in path optimization. Snake algorithms, for instance, need to be fed with a generic image energy, which is derived through more or less complex filtering operations like a gradient amplitude map, Laplacian map, distance transform, etc. On the other hand, road tracking algorithms do not include any topological information about the connectivity of the road network. Disturbances due to background objects or noisy images (like SAR images) lead often to very wiggling tracks or even useless results. In such situations, snakes and in particular network snakes show clear advantages over tracking procedures, since the geometric and topologic constraints involved in the optimization process act as regularization for the noisy data (Butenuth & Heipke 2010).

Fig. 5: User-assisted road tracking in an IKONOS image taken during the Elbe flooding in Germany, 2002. Yellow points: tracked road sections; blue lines/red points: user clicks.

Fig. 5 shows an example for user-assisted tracking of a main road in an IKONOS image taken during the Elbe flooding in Germany, 2002. The yellow parts were traced automatically, while simple user clicks were asked at the blue positions. Here, the operator had to decide whether tracking should just continue or interactive editing is necessary. Tracking could continue at all interruptions except the one shown in the detail of Fig. 5. It illustrates a situation, where cutting-off the tail of the track and manual digitizing of a short road section is necessary due to the occlusion of a small cloud. A detailed description of this algorithm and the variety of options for user interaction can be found in Baumgartner et al. (2002).

At this stage of processing, the road network has been categorized into reliable and unreliable parts, i. e., "green" and "red" road portions only, since the "yellow" parts have been assigned interactively to one of these classes. In addition, potential gaps – which can only occur when applying an automatic road extraction at the beginning of processing – have been closed. In the next section the centerlines of reliable roads are geometrically refined.

3.3 *Road Refinement*

The availability of road data as input information for the assessment requires a high geometric correctness of the road network, in particular for the aimed subsequent classification approach. This prerequisite cannot be ensured in general and, thus, network snakes (Butenuth 2007, Butenuth & Heipke 2010) are used for the geometric refinement of the road network. Network snakes are based on the well-known active contour models (Kass et al. 1988), but in addition to the image energy and internal energy the topology is introduced into the optimization process. This graph-based active contour method enables a complete topological and shape control during the object delineation. The exploitation of the topology during the iterative optimization process enables to deal with fragmented and blurry object representations in different kinds of imagery (Butenuth & Heipke 2010).

Network snakes are applied to the geometric refinement of road networks to improve and correct the database if necessary. The proposed approach is either able to deal with roads from a database as initialization in an automatic system or, alternatively, within an interactive framework to derive a geometrically optimized road network. In addition, the optimization of roads using network snakes can be accomplished with different kinds of image data such as optical and SAR-data, because the method is able to cope with varying image energy terms in the flexible minimization process. In general, the refinement is accomplished as a preprocessing step using image data representing a status of intact roads. However, in Fig. 6 the network snakes approach is applied to the non-flooded roads starting from the initialization (blue) moving step by step (white) to the true positions of the roads (red) in the optical image. The benefit of network snakes is the exploitation of the topology during the graph-based optimization together with the image energy and the internal energy being a powerful method to deal with noise or disturbances in the imagery when refining road networks. Furthermore, only the local image information at the network has a purposive effect to the correct result, because the region-based image information within the enclosed road network segments is not useable due to the different object classes (e. g., settlement).

3.4 *Road Classification*

The aim of the third module is the assessment of a road network concerning their functionality after a natural disaster. The prerequisite for the road classification is an up-to-date and geometrically correct road network. Most of the industrialized countries offer road databases which fulfill the required geometrical accuracy and up-to-dateness. If there is no appropriate road network available the modules described above can be applied to extract/update roads or refine already existing road networks.

In Fig. 7 a generic overview of the damage assessment system is given. Since the reliability and up-to-dateness of the assessed road network is of prime importance it is necessary to embed all kind of information which is available in near-realtime. Therefore the de-

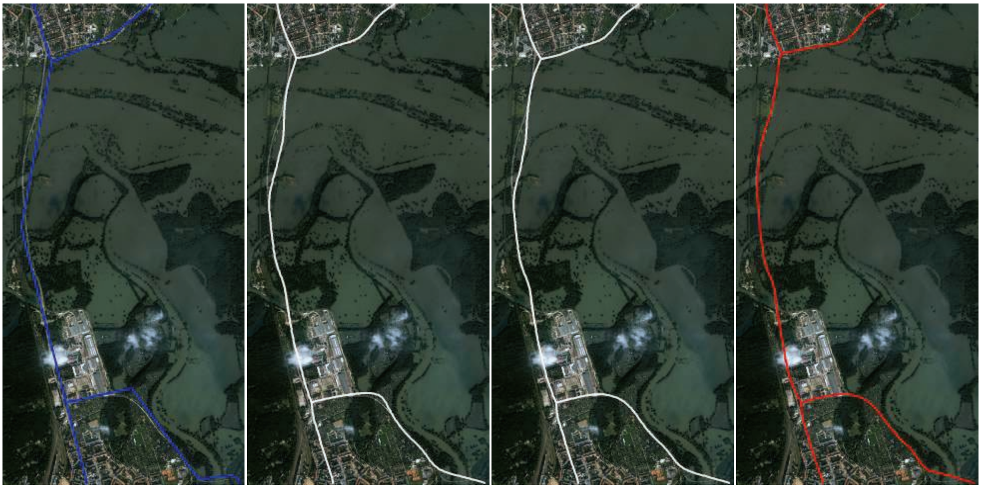

Fig. 6: Automatic road refinement using network snakes in an IKONOS image taken during the Elbe flooding in Germany, 2002: initialization (blue), optimization steps (white), result (red).

sign of the assessment system has an flexible stucture. The main contribution in the proposed damage assessment system results from different kinds of imagery. Beside optical and radar imagery also additional information such as a DEM can be embedded into the system (Frey & Butenuth 2009). Furthermore the system can cope with imagery at different time points. The useage of multi-temporal data can further improve the results as shown in Tab. 1 (Frey & Butenuth 2010).

The basic idea of the system is the derivation of probabilities from each individual input data whether an road object is trafficable or not. The methods used to infer the probabilities depends on the available input data. In case of optical imagery a multispectral classification is carried out using Gaussian Mixture Models (GMM) (McLachlan & Peel 2000). The road segments given from the GIS-database are classified in various classes such as *intact road*, *not intact road* and all possible kinds of occlusions of the roads such as *forest*, *clouds* or *shadows*. The appearance of the class *not intact roads* depends of the natural disaster. For example in case of a flodding the class *not intact roads* is replaced by the class *water*. The radiometric appearance of the class *intact road* has large variations. This leads to probability density function with a large standard deviation. The difficulties which arise dealing with the broad probability function can be reduced using Gaussian Mixture Models. The complex probability density function composed of several multivariate normal distributions is therefore a more suitable statistical representation of the class *intact road*. Using the Gaussian Mixture Model every road segment is assigned a probability p_{img} belonging to a previous defined class. If a maximum likelihood classification assigns a road segment to class which describes the occlusion of a road (*forest*, *cloud*) than further information has to be exploited. It is possible to utilize the results from the classification of adjacent road segments. Also further input data can give additional hints if the occluded roads are intact or not. In case of flooding the DEM can give additional hints if roads are flooded or not. Belief functions are used to derive the probabilities from these additional informations such as DEM. In case of floodings it is assumed that roads higher than a threshold a_2 are certainly trafficable and lower than

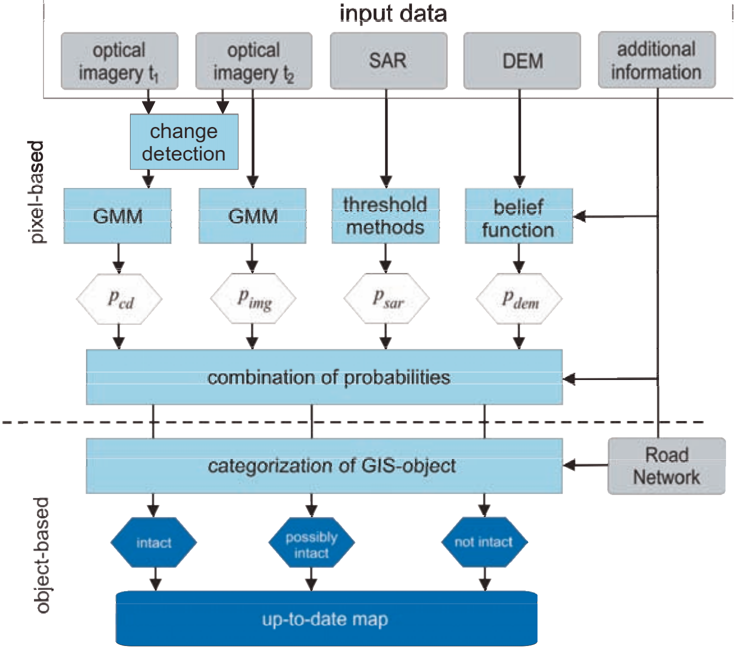

Fig. 7: General damage assessment system.

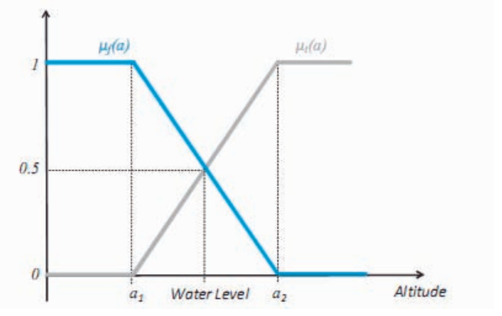

Fig. 8: Belief functions for roads after flooding.

a threshold a_1 are certainly flooded. The probabilities inbetween these theresholds are modelled with a linear function (cf. Fig. 8). The blue function $\mu_f(a)$ shows the belief function that a road is flooded. The gray function $\mu_t(a) = 1 - \mu_f(a)$ stands for the probability that a road is trafficable. By means of the belief functions a probability p_{dem} can be assigned to every road segment.

The availability of mutli-temporal imagery can be used to carry out change detection. In the proposed approach the Multivarate Alterationn Detection (MAD) method was used, since it is invariant to linear transformation (Nielsen et al. 1998). Therefore linear changing in atmosspheric conditions or sensor calibrations can be neglected. The result of the MAD method are so called MAD variates for each pixel which represents different kind of changes. In case of floodings a training sample is choosen which represents the change from flooded road to a trafficable road or the other way around. By means of the trainings set a supervised classification of the MAD variates using Gaussian Mixture Models is carried out to calculate the probabilities p_{cd}. The probability p_{cd} give additional hints if a road segment is flooded or trafficable at time point t_2. The combination of the probabilities derived from different input data is carried out by a multiplication of the probabilities p_{img}, p_{cd} and p_{dem} embedded into a rule based framework which depends on the natural disaster.

The result of the damage assessment system applied to the Elbe scenario is depicted in Fig. 9. Two IKONOS-scenes from two time points t_1, t_2 and a DEM from ATKIS with an 10 m grid and a geomtrical accuracy of +/− 1m was used as input data. The road segments are categorized into three states *trafficable*, *possibly flooded* and *flooded*. The state *possibly flooded* means that the automatic assessment system could not categorized the road segment within a required certainty.

The obtained results are compared to a manually generated reference. The generation of the reference is carried out by means of the information on image at time t_2. Therefore, it is not a comparison with the real ground truth, but it is the comparison of the automatic approach with the manually interpretation of an human operator. The reference is categorized into three different states *trafficable*, *possibly flooded* and *flooded*. Since the categorization of the automatic system consists of the same states the following four different assignment criteria are determined: 'correct assignment', 'manual control necessary', 'possibly correct assignment' and 'wrong assignment'. The category 'correct assignment' means that the manually generated reference is identical with the result of the automatic system. In the case of 'manual control necessary' the automatic approach leads to the state *possibly flooded* whereas the manual classification assigns the line segments to *flooded* or *trafficable*. The other way around denotes the expression 'possibly correct assignment'. 'wrong assignment' means that one result categorize the segment to *flooded* and the other to *trafficable*. The en-

Tab. 1: Results and evaluation of the assessment system: Evaluation of road data of the Elbe test scenario exploiting different input data.

	t_2	t_2, *DEM*	$t_{1,2}$, *DEM*	$t_{1,2}$, *r*, *DEM*
Correct	68.40 %	68.45 %	69.60 %	87.14 %
Manual	27.88 %	27.77 %	27.48 %	10.96 %
Possibly	2.64 %	2.72 %	2.52 %	1.79 %
Wrong	1.08 %	1.06 %	0.40 %	0.11 %

Fig. 9: Detail result of the assessment system using all available input data: image t_1, image t_2, DEM and manual generated reference at time t_1; green = trafficable, yellow = possibly flooded, red = flooded, dark blue = trafficable (changed from flooded at time point t_1 to trafficable at time point t_2).

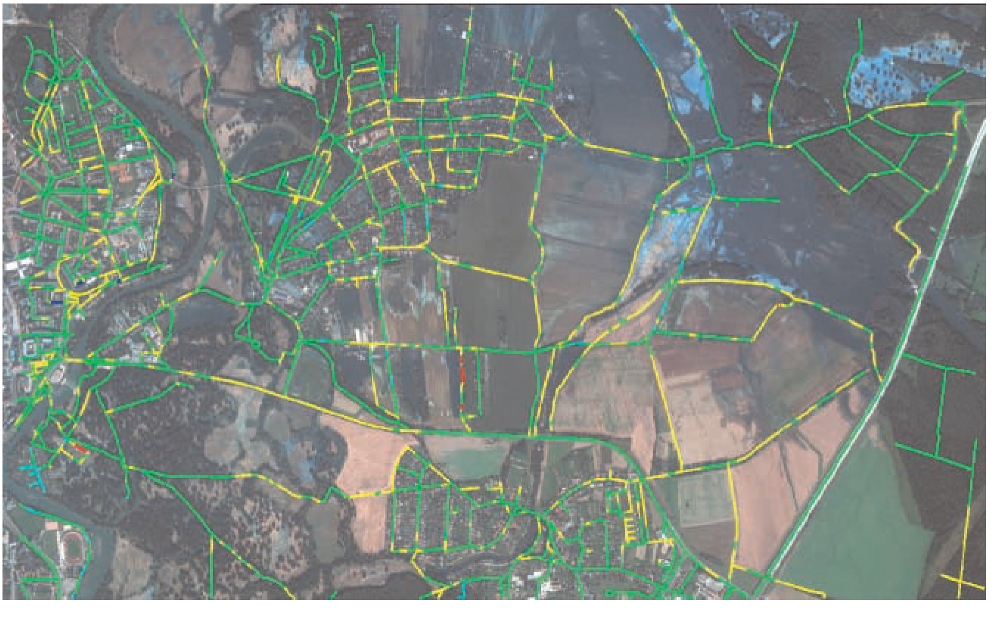

Fig. 10: Evaluation of the assessment system using image t_2, image t_1 and DEM; green = 'correct assignment', yellow = 'manual control necessary', cyan = 'possibly correct assignment', red = 'wrong assignment' [system = trafficable, reference = flooded], dark blue = 'wrong assignment' [system = flooded, reference = trafficable].

hancement of the automatic system by the combined interpretation is shown in Tab. 1.

The first column in Tab. 1 represents the result using only the image t_2 without any further information. The result with about 1% of 'wrong assignments' and about 68% 'correct assignment' is almost identical if an additional DEM as input data is used (cf. Tab. 1: t_2, *DEM*).

In Fig. 10 the result of the third column from Tab. 1 is visualized which includes the additional scene at time point t_1 as input data. Green road segments correspond to 'correct assignment', yellow to 'manual control necessary', cyan to 'possibly correct assignment' and red or blue belongs to 'wrong assignment'. If the system assigns a road segment to the category *trafficable* but the reference is *flooded* the road segment is colored in red. Dark blue road segments are assigned to *flooded* by the system and *trafficable* by the reference.

The forth column (cf. Tab. 1: $t_{1,2}$, *r*, *DEM*) shows the results exploiting an additional manually generated reference at time point *t1*. The results are by far better then the previous obtained results. The major reason for the improvement follows from the assumption that trafficable roads at time point t_1 are also trafficable at time point t_2. The assumption can be made since the flood was receding. The 'correct assignments' arise from 69% to 87% and the 'wrong assignments' decrease from 0.4% to 0.1%. But it is important to point out, that a correct reference at the time point t_1 has to be generated. Nevertheless, it has no influence of the fact that the system is near-realtime since the time consuming generation of the reference can be done at time point t_1.

4 Conclusions

In this paper three modules dealing with the automatic extraction and updating, the refinement and the assessment of roads are presented. The different modules are investigated regarding their usability in case of natural disasters. The automatic extraction of roads based only on the image information cannot deliver reliable information which is needed in case of natural disasters. However, the automatic extraction can speed up the semiautomatic extraction of accessible roads. Furthermore the updating and refinement of existing GIS road data are crucial methods in order to get a complete, up-to-date and geometric correct road network which is a prerequisite for the final damage assessment.

In future work the damage assessment system will be improved using a consistent statistical framework. Up to now, the combination of the derived probabilities is embedded into a rule-based framework. This framework will be substituted using the statistical theory of Dynamic Bayesian Networks. A special Dynamic Bayesian Network and promising graphical model are Hidden Markov Models.

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