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AN ATTEMPT TO ATTAIN NEW INFORMATION IN RECONSTRUCTION OF ROAD TRAFFIC ACCIDENTS APPLYING DIGITAL IMAGE PROCESSING

ABSTRACT

Court expertise dealing with the reconstruction of road traffic accidents often have to take into account the possibility that an accident could have been a set-up. Such suspicions can be eliminated only by considering all the evidence material from the accident scene. In case of photographic material experts come across the missing material, bad lighting, lack of contrast, different angle perspectives, blurring, omitting important details, etc. Therefore, different methods in forensics image processing have been developed. Most of these methods are primarily used in the processing of different types of photographic material, but some can be applied in the field of road accidents analyses. This paper shows the implementation of digital image processing methods used for processing of remotely sensed imagery.

Even though the photographic evidence is incomplete, it is possible to determine the position and dispersion of different materials. This gives the experts additional information that can help in understanding with relatively high probability if the collision between vehicles occured at all and if it did, where. The paper consists of the presentation and description of methods used for digital image processing in a real case study while reconstructing the road accident.

KEY WORDS

road traffic accidents, forensics, induced traffic accidents, image classification, digital image processing

1. INTRODUCTION

Image processing in forensics has been neglected in the past. As technology progressed in the last two decades the field of digital imaging methods and image analysis technologies gained far more in importance [1]. Technical improvements of digital cameras and video cameras played a key role in developing new algorithms and software applications for digital image processing. Primarily, these were used in forensics in the field of fingerprint recovery and analysis as well as in the field of lab crime scene reconstruction [2]. The basic procedures of forensic image processing include different image enhancement methods, patterns recognition, image reconstruction, image comparison, etc. Procedures vary according to the field of implementation.

The field of road traffic accidents analysis and reconstruction is a special field in forensics. Accident analysts deal mainly with image processing that enables finding answers about the position, shape and size of the objects in the image. The pieces of information are useful for designing the layout of the accident site as well as the 3D (three-dimensional) images of vehicles which make it possible to assess damage dimensions. Glass is a material frequently present at the scene of such events. One of the problems analysing forensic evidence such as glass fragments is the determination of glass distribution pattern. Many times the accident analysts also face the uncertainty about whether the vehicle collided with another object or not, or in other words, whether the accident was a set-up or not. The characteristics of such accidents are usually nighttime, remote place and no human casualties. Police reports and accident drafts are scarce, and they do not include all details on collision traces. In such cases it is very useful if one can apply a forensic image analysing method which makes it possible to define information showing the collision consequences. This is one of the few possibilities to get the answer to such doubts. Presenting a case in which such method was used is the aim of this paper.

2. DIGITAL IMAGE CLASSIFICATION

Classification of the image is a method based on the recognition of spectral response of the object. This method is rarely used in forensics, especially in road accident analyses. Just a few cases of the application of such approach are presented in literature [1-4], mostly in processing of narrow band photographic images as a result of object analysis with chemical reagents, which improve the visibility of typical spectral features of certain natural substances (e.g. blood, latent fingerprints).

The classification procedures with automatic classification based on spectral information of one pixel are called spectral pattern recognition [5]. The classification of digital image is a process widely implemented in processing satellite images, especially in defining the land cover type of a geographic area. This process requires grouping of objects considering maximum likelihood of objects in one group as well as maximum difference between objects from different groups [6].

Objects are classified based on their spectral response in different spectral bands. Various radiation features of the object result in various combinations of numeric values of the pixel for each spectral band separately, which forms a spectral pattern.

There are two basic approaches to the classification process. Unsupervised classification is more automatic and is based on discovering the statistical patterns among data. Supervised classification, on the other hand, consists of the training phase and the classification phase. During the training phase the classifier defines a representative site for each object (training sites). According to these patterns a set of statistics is determined, describing a spectral pattern for each object. Later, in the classification phase, each pixel is distributed to one appropriate group considering the likelihood of its spectral pattern [5, 6].

Maximum likelihood method is one of the main classification methods. It falls into the group of supervised methods and is a deterministic method with hard criteria. This method is based on the probability density function associated with the training site signature, so a spectral homogeneity of each training pattern is very important when a multispectral classification approach is applied. In the classification process a value is assigned to each pixel in accordance to the highest probability of the group. This method is particularly appropriate when it is possible to define reliable training patterns. More about this method can be found in [7].

Reliable training sites can be recognized in almost every occasion when analysing road traffic accidents, thus the supervised classification process is more appropriate. In this paper we try to explain the possibility of implementation of the procedures that are widely used in satellite image classification, which we successfully used for recognizing the car glass dispersion pattern.

Beside the maximum likelihood method some other methods from the group with soft classification criteria were used for the purposes of our sample image classification. One of these is the so-called BELCLASS classification method which is based on *Dempster-Shafer theory*. This method allows for the expression of ignorance in uncertainty management [8]. The prime use of this method is to check the quality of training site data and the possible presence of unknown classes. The basic assumptions of *Dempster-Shafer theory* are that ignorance exists in the body of knowledge, and that the belief for hypothesis is not necessarily the complement of belief of its negation. The degree to which evidence provides concrete support for a hypothesis is known as belief, and the degree to which the evidence does not refute that hypothesis is known as plausibility. The difference between these two is the belief interval, which acts as a measure of uncertainty about a specific hypothesis [9].

3. CLASSIFICATION OF SAMPLE IMAGE

Car glass residuals as well as other parts of the vehicle that have fallen off during collision are very important elements for reconstruction of the road accident site. Recognition of these on photographic evidence material in most cases represents a big problem to court experts dealing with reconstruction. It is very common that crushed car glass mixes with the tiny gravel on the road surface (especially in crossroads) which makes it even more difficult to recognize its dispersion. In order to make our test sample as realistic as possible we mixed crushed car glass with gravel on a partially wet asphalt surface. The original digital image of our sample is shown in *Figure 1* A, where the actual car glass dispersion can be seen.

The application of chosen methods was tested on two examples. Digital photos were taken from two perspective angles: from the plan view and from the central perspective view. All procedures of digital image processing were executed in the software tool *Idrisi 2.0* (*Clarks Lab*).

Sometimes it is necessary to process photographic material prior to the classification process. This is done to enhance the image and enable better visual interpretation. The pre-classification process can consist of procedures as histogram change, filtering, colour/contrast adjustment, noise removing, etc. Our sample image was of high quality, so these procedures were not necessary. The first and very important step of the supervised classification process is the definition of training patterns. These were defined according to

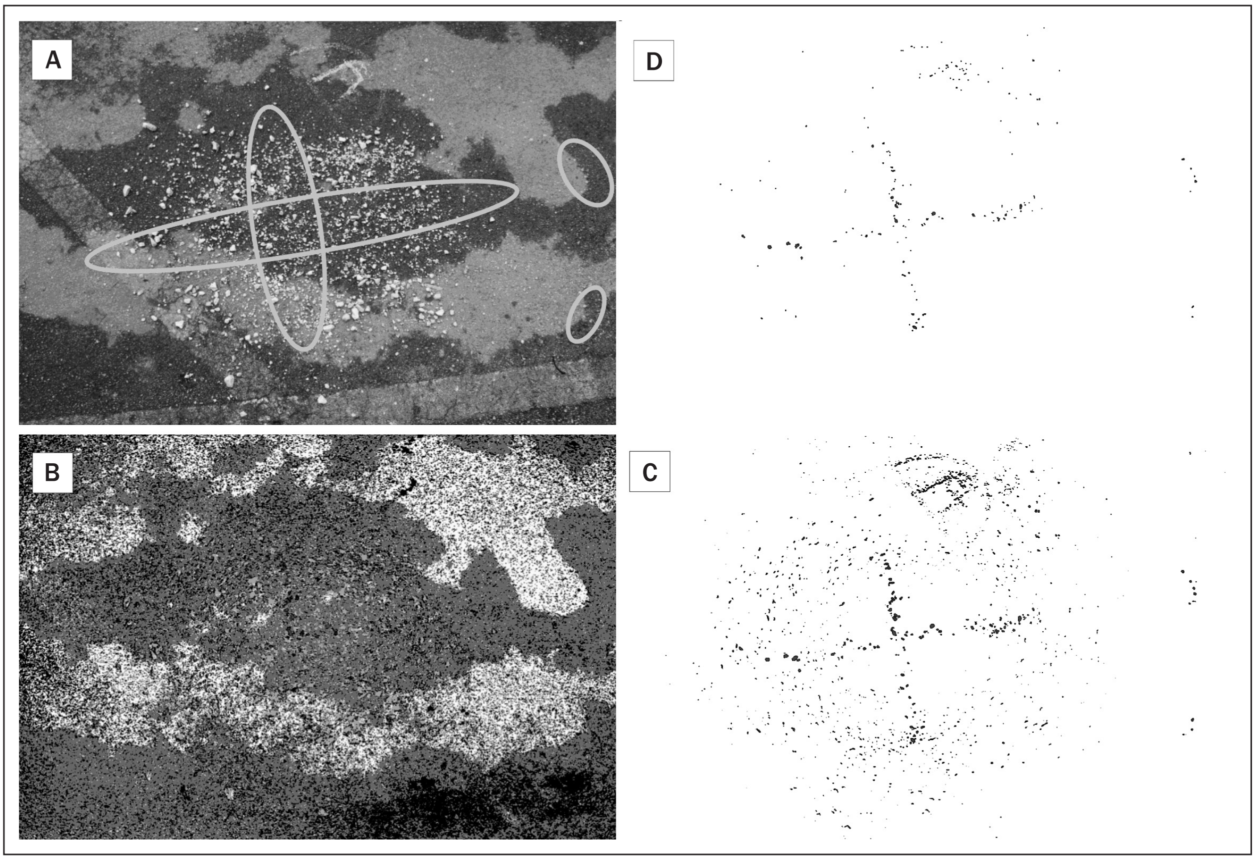

Figure 1 - Classification using maximum likelihood method: A - original digital image, B - classified image, C - classified image (car glass), D - classified image (filter min 3x3)

the known position of the car glass in our sample, so they could be treated as homogenous and reliable. The same training pattern was used in all classification types.

When classifying our plan view digital image, the maximum likelihood method was used first. *Figure 1* shows the steps taken to finally attain a filtered classified image of car glass showing the dispersion pattern. The classifier probability whether a pixel belongs to a particular category class were set to 0.95. The variance of within-class spectral response is shown in *Table 1*.

Table 1 - Values for spectral response of pixels assigned to different classes

Classes	Mean	STD
wet asphalt	85.957	44.8383
not classified	113.306	30.4787
asphalt	147.461	28.0083
glass	163.105	26.6051
gravel	213.664	19.4055

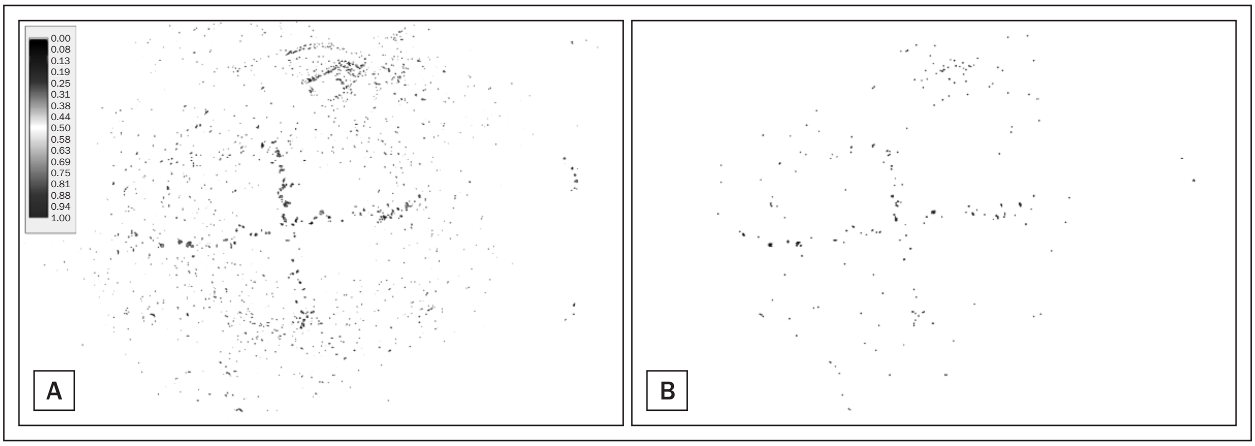

Figure 2 - Classification using BELCLASS method: A - probability of car glass, B - classified image

The BELCLASS method was used on the same digital image in order to make a comparison of the classification results. *Figure 2* shows two steps in BELCLASS classification procedure; it seems that the final step gave results very similar to the previous classification.

The same steps were used to check the possibility of repeating the procedures of two classification methods and their results with our second central perspective view image of the same training site. The classification results following the maximum likelihood method and later the BELCLASS method are presented in *Figure 3*.

According to the view angle and new perspective, the classification results showed a very similar pattern of glass dispersion in both cases, when using maximum likelihood method and later BELCLASS method. However, further comparison of the two methods used was made to define the one more reliable in this case.

3.1 Comparison with the actual car glass dispersion

Comparison of the effectiveness of both used methods was possible since the realistic data on the carglass position in our sample were known. The classification error matrix and the crosstable *Crosstab* were used to estimate the classification reliability. Crosstabs also give a degree of association and *Kappa statistics* based on the *Chi square value*. The matrix helped us to determine the relationship between reference (realistic) data and classification results. In our case the classification error matrix is a good indicator of classification reliability, even though it is based on the training patterns and it only shows how successful a classification of one defined sample area can be when using training statistics in this area. Direct comparison of classification results reliability for both methods was possible only after the BELCLASS method results were modified. This was done by adding an attribute of maximum probability class to each pixel upon its probability value. The results of this comparison are shown in *Figure 4* and *Table 2*.

Table 2 - Summary of Crosstab results

Value	MAXLIKE	BELCLASS
Chi Square	3,329,613.50	1,234,060.250
P-Level	0.0000	0.0000
Cramer's V	0.6466	0.3937
Overall Kappa	0.5897	0.3628

The reliability study results showed that a contingency exists between the reference data and the classification results. The values of *Cramer's coefficient V*

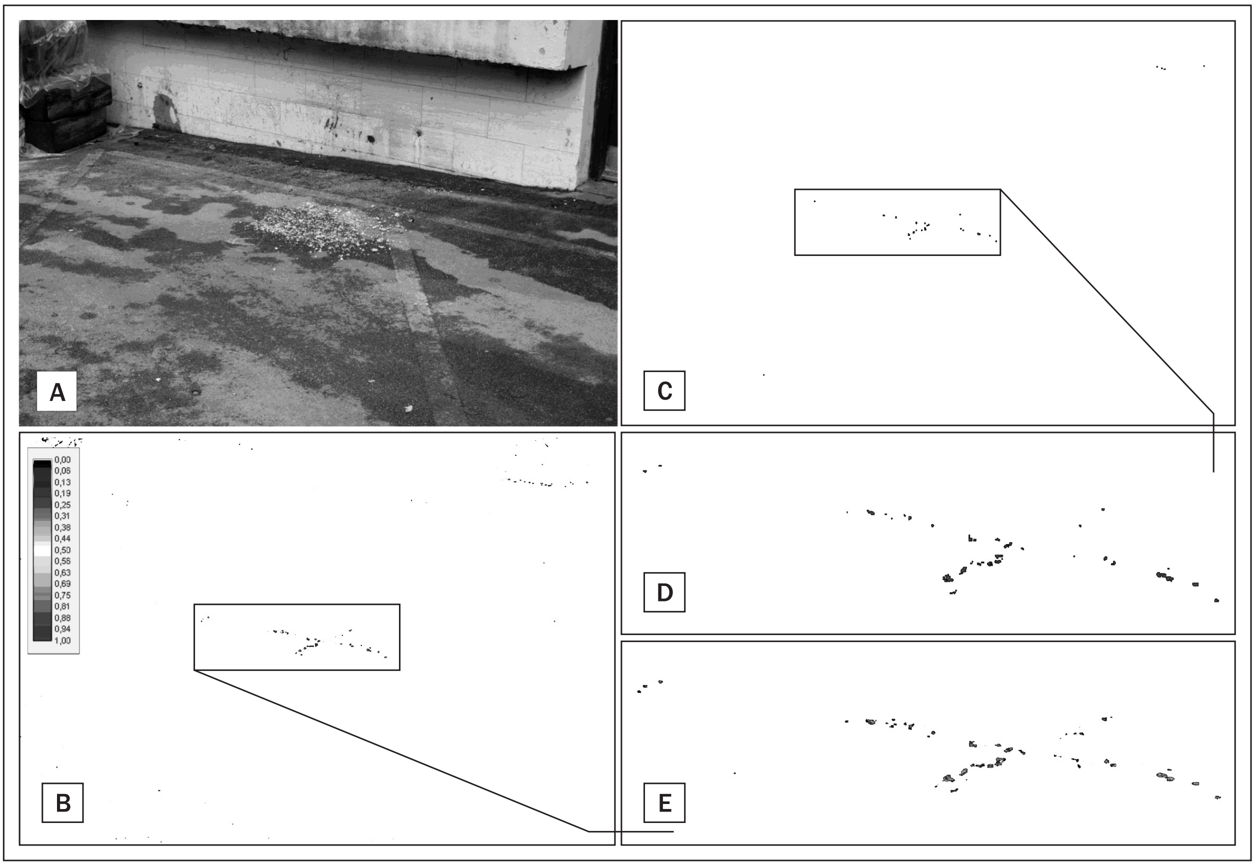

Figure 3 - Classification of central perspective view image: A - original digital image, B - classification with BELCLASS method (E), C - classification with maximum likelihood method (D)

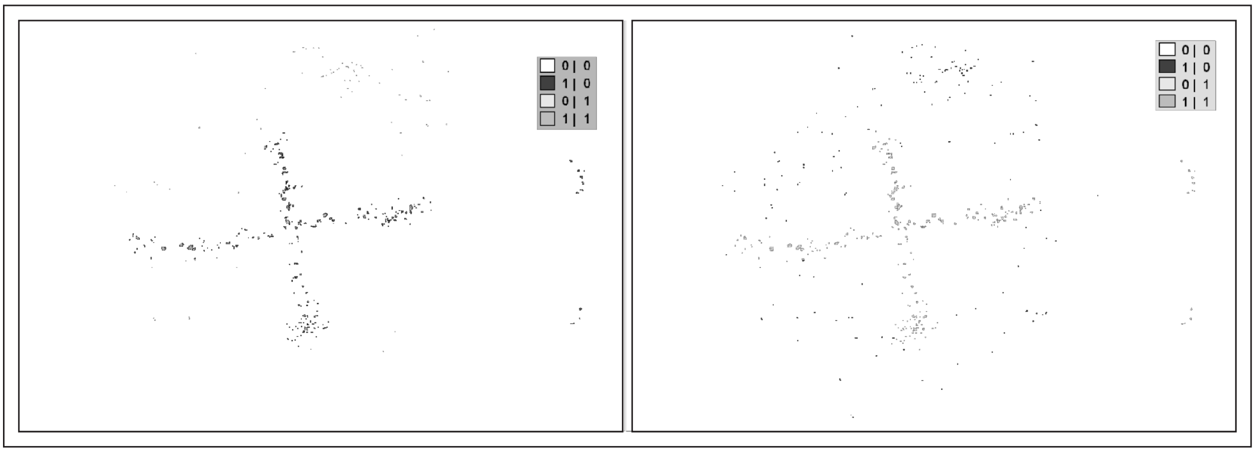

Figure 4 - Classification reliability: A - maximum likelihood method vs. realistic dispersion, B - BELCLASS method vs. realistic dispersion

and *Kappa statistics* are higher in maximum likelihood method, hence this method turned out to be more reliable. Kappa statistics value tells that the classification using maximum likelihood method is 58 percent more reliable than the randomly classified data. The results of comparison between two or more methods can be very different from case to case; thus, when interpreting them, one has to be very careful. Sometimes the analysis also shows that using a soft classification method over the hard classification method makes much more sense since the classification with soft criteria enables deduction upon the statistical probability.

4. EXAMPLE OF METHOD IMPLEMENTATION AT ACCIDENT RECONSTRUCTION

The described methodology was implemented in a case study to give an example of its applicability in reality. We chose the case that was estimated as a set-up by the insurance expert, who was comparing the damage of the vehicles involved in the accident. There was a statement in the police report that the accident occurred in the crossroads; however, there was no collision point documented in the police drafts. The analysis of the photographic material showed damage that could have occurred during vehicles collision. A stronger proof of the actual collision occurrence as well as the definition of the speed at the time of collision would be possible if the exact point of collision was determined. There were only a few photographic images of the accident that were suitable for such an analysis.

The most adequate image proved to be the one shown in *Figure* 5A. A question arose if the crumbled material at the bottom right part of the image was gravel or crushed car glass indicating the track of the place of collision occurrence. We wanted to answer this question by processing the image.

The processing started with the procedure of changing the histogram of colour bands. This enabled the enhancement of the car glass spectral response, which is shown in *Figure* 5B. The classification process began with the definition of training patterns. The image was divided into quadrants considering that the illumination conditions were not uniform and these can affect spectral signatures of pixels in different segments of the image. The training patterns were then defined for each quadrant. The quality of training patterns varied a lot, but this was expected. Lower quadrants had only two training patterns: gravel and car glass. The training patterns in these quadrants were of relatively good quality, whereas those in the middle part quadrants were of poor quality. The method of maximum likelihood was used for classification. This pointed out some quadrants where the spectral signatures of car glass interfered with spectral signatures of other materials (especially in the middle part quadrant with a lot of reflections from the car itself).

The problem was solved by using different operations on the classification results. First, all pixels assigned to class *glass* with posterior probability lower than 0.95 were reclassified in value class *other material*. Then a Sobel edge detector filter of 3x3 cell size [10] for detecting the edges was used; after that the texture convolution filter was used to analyze edges with specific directions. The vertical edges were eliminated since the probability of crushed car glass or other solid material holding up to vertical surfaces is very low.

After classification the quadrants were reassembled. In post-processing of the classified image the density centroids of car glass dispersions were pointed out, which made the definition of the collision point more probable. It turned out that there were two centres: one on the vehicle's top and the other on the road surface (*Figure 5D*).

The digital image processing proved the existence of the crushed car glass traces, which can be evidence of the actual collision occurrence in the crossroads

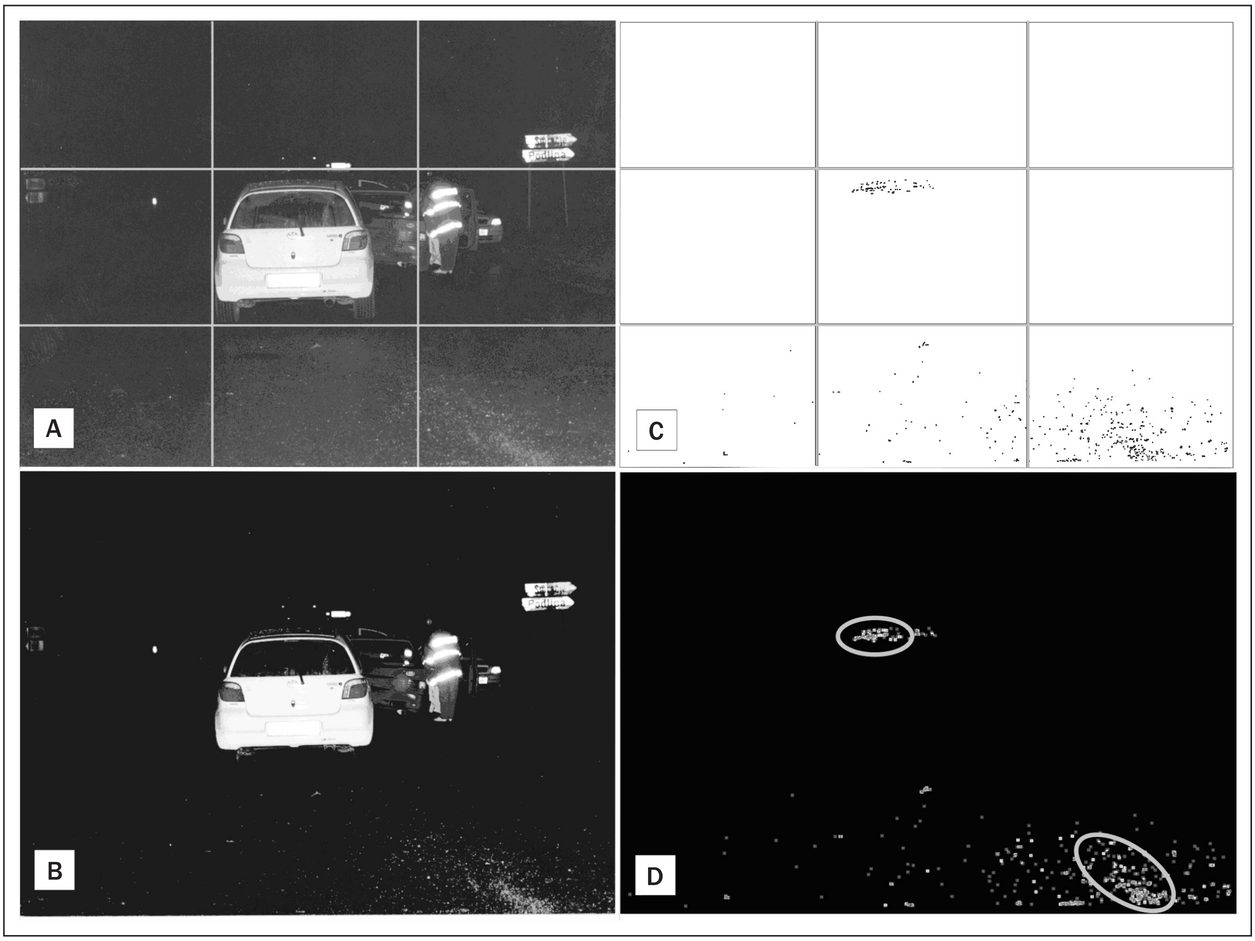

Figure 5 - Classification of the case study image: A - original image and the quadrants, B - image enhanced before processing, C and D - results of classification

itself. It is less likely that the car glass was strewn intentionally after the accident by individuals involved in the accident in a way and in the spots shown in *Figure 5D*. Whether the collision occurred intentionally or not, is not susceptible of proof. Since there were no reference data to make a comparison and validate the training sites with the results, one has to be very cautious when interpreting the results.

In addition we tried to analyse the direction of the glass dispersion pattern, however it turned out that none of the used surface fitting trends was statistically significant (*Figure* 6).

Figure 6 - Spatial trend of glass dispersion (linear trend - R^2=0.047; F=14.79; df=598; df=2) polynomial third degree (r^2=0.1; F=7.92)

5. CONCLUSION

Every additional information can be important and crucial in reconstructing road traffic accidents. The paper showed how an adequate processing of the digital photographic material can bring results representing new and important information for the accident reconstruction. It is important to note that the procedure is documented and can be reproduced if necessary. Moreover, the implemented methods proved to be of greater importance when the quality of the photographic material is poorer. However, the methods presented have some limitations. In situations where it is impossible to attain reliable training sites, the methods will perform poorly. Another limitation could be the quality of photographic material. If the photographic material is of poor quality, this method will not give reliable results.

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POVZETEK

POSKUS PRIDOBIVANJA DODATNIH INFORMACIJ ZA REKONSTRUKCIJO CESTNIH PROMETNIH NESREČ S POMOČJO PROCESIRANJA SLIKOVNIH DOKAZOV

Pri cestnih prometnih nesrečah se pogosto pojavi vprašanje, ali je mogoče, da je nesreča nameščena. Pri iskanju odgovora na tako vprašanje si lahko sodni izvedenec pomaga samo z materialom, zajetim na mestu nesreče. V primeru fotografskega materiala se izvedenci srečujejo z materialom pomanjkljivega obsega, slabo osvetlitvijo, kontrastom, različnimi perspektivami, slabo ostrino, izpuščenimi pomembnimi podrobnostmi. Prav zaradi tega so se v forenziki uveljavile različne metode obdelave digitalnih slik. Čeprav so te metode primarno namenjene obdelavi fotografskega materiala drugačnega tipa, lahko nekatere apliciramo tudi na področje analize prometnih nesreč. Prispevek poskuša predstaviti uporabnost metod digitalne obdelave slik, ki jih uporabljajo pri obdelavi posnetkov daljinskega zaznavanja.

V primeru pomanjkljivega fotografskega materiala je možno s pravimi postopki in različnimi načini obdelave digitalnih slik ugotoviti lego in razpršenost različnih materialov. Na podlagi tako pridobljenih dodatnih informacij je v nekaterih primerih mogoče z veliko verjetnostjo ugotoviti, ali je prišlo do trka vozil, in določiti približno mesto trka. V prispevku so na konkretnem primeru predstavljene in opisane metode procesiranja digitalnih slik, ki smo jih uporabili pri rekonstrukciji prometne nesreče.

KLJUČNE BESEDE

cestne prometne nesreče, sodno izvedenstvo, klasifikacija digitalnih podob, digitalna obdelava fotografij

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