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COMPUTER VISION SUPPORT TOOL FOR ASSESSING CONCRETE HYDRO-DAMS SURFACE DETERIORATION

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Abstract: *Hydro-dams failure risks should be continuously assessed since they are critical for environment/society. A key component of the dam monitoring regulations is visual inspection, which should allow objective measurements of their structural condition evolution. Towards this goal, computer tools should be developed, using artificial vision. For concrete hydro-dams, an important issue is the examination of the downstream surface deterioration. This paper proposes a computer vision tool to assist experts in generating visual surveillance reports in respect to the quantitative and linguistic assessment of the deterioration and erosion of concrete. Compliant with the human observation, the results prove the system's functionality.*

Keywords: *dam surveillance, computer vision, visualization tools, fuzzy knowledge representation*

1. INTRODUCTION

Surveillance and monitoring of the hydro-dams condition and evolution in time represents a serious environmental problem, since the consequences of their failure can dramatically affect the environment and humans. The importance of periodic surveillance, by objective measurements and subjective observations, along with the experts' interpretation of the acquired and observed data, is emphasized by existing international measurements and observation standards. Well defined surveillance and monitoring strategies and guidelines exist, specific to the hydro-dam type (a good survey can be found in (CSED, 1983). In these strategies, it is clearly stated that an important task in the hydro-dams surveillance process is the visual inspection. It is one of the main methods for evaluating the dam's state, allowing decisions to be made about dam behaviour, based on direct observations. Visual inspections complement the data analysis process concerning different sensors and transducers placed within the dam body and it's surroundings, and the observations are filled in a record describing the inspections concerning: reservoir, banks and slopes, concrete structure, downstream valley. It is also recommended to store digital images of the inspected structures for objective assessment of the observed issues (DSC, 2003).

Many artificial intelligence systems have been developed for dam surveillance applications. They mostly cover knowledge-based (expert) systems and neural network approaches. In (Sieh, *et al.*, 1988) a KBS is described, developed to assist in the diagnosis of seepage from embankment dams. The system attempts to define the type of problem (point source seepage, non-point seepage, sand boils, sinkholes, and drain flow), the seriousness of the problem and a recommended course of action. Another KBS, (Asgian, *et al.*, 1988), is constructed as a diagnostic tool for seepage problems associated with various types of dams. In (Ohnishi and Soliman, 1995) a neural network approach is implied to investigate seepage under a concrete dam founded on rock. Dam permeability is estimated with neural network based systems (Najjar, *et al.*, 1996). A bionics model of dam safety monitoring was proposed in (Wen, *et al.*, 2004). The proposed monitoring system for dam safety is composed of integration control, inference engine, database, model base, graphics base, and input/output modules.
In respect to the computer vision based implementations of visual observations on hydro-dams structures, the situation is slightly different. Although visual inspection plays an important role in the examination of these structures, few computer vision-based systems for the assisted diagnosis of hydro-dams exist, among these, (Blain, 2001; Battle *et al.*, 2003; Takagi, *et al.*, 2000) are worth to be mentioned here.

One of the issues addressed during the visual inspection of concrete hydro-dams, important in the preservation of a good condition of the concrete, is the examination of surface deterioration in respect to small patterned cracks and roughness on the downstream wall. These types of superficial defects can indicate that surface is prone to structural faults (CSED, 1983). This kind of assessment is particularly a type of task where digital image enhancement and analysis can bring significant benefit, not only by presenting the user with a more relevant image of the hydro-dam wall in respect to the surface deterioration, but also by providing – through suitable selected numerical descriptors, correlated with linguistic descriptors – subjective and examiner-independent information about the surface state, that can be stored and used as a reference in measurements done at a later time.

This paper describes the implementation and validation of a computer vision tool, enhanced with expert gathered information, to assist human evaluators in the assessment of concrete dam wall surface deterioration. To gather and make efficient use of the expert knowledge, sample images are used and a training module is designed. To numerically quantify the deterioration of the hydro-dam downstream wall surface, a fuzzy edge classification and edge density – based computation is implemented as feature extractor, as in (Gordan and Georgakis, 2006). The proposed and implemented system was verified on a set of hydro-dam downstream wall images acquired from the Tarnita hydro-dam in Transylvania, Romania, showing good performance (compliant to the human observer).

2. THE APPLICATION FRAMEWORK FOR DAM SURVEILLANCE/MONITORING

The proposed computer vision tool is part of an integrated system that supports the decision processes regarding dam safety. It consists of complex integrated hardware/software modules: measurement equipments, intelligent databases and software applications; these are able to provide a complete "image" of the dam's parameters anytime anywhere. The global architecture of the decision support system is presented in Figure 1.

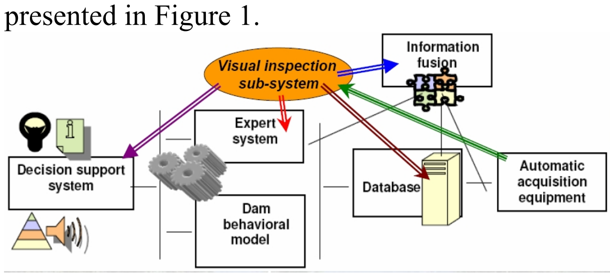


Fig.1. Integrated system for dam safety decision support

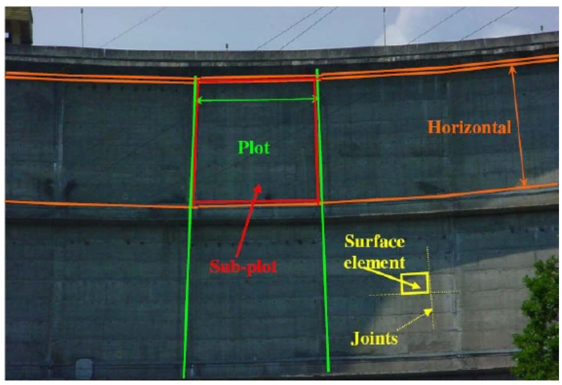


Fig..2. Image decomposition into basic elements.

The geometry of each sub-plot is described by the number of surface elements delimited by joints between the concrete blocks that compose each sub-plot. Thus a sub-plot image contains N_H x N_V surface elements

All data provided by the acquisition equipments (including tele-pendulums, automatic acquisition stations, visible and infrared cameras) is stored into a multimodal database. The image analysis algorithms presented here are applied to downstream dam wall surface examination, on images acquired with visible spectrum digital cameras.

The software sub-system for visual inspection performs the following tasks: (1) management of the visual inspections records; (2) image pre-processing (allows for the de-composition of the image, as shown in Figure 2, into parts defined by the intersection of dam's plots and horizontals – we will call here each of these parts, sub-plot – and on surface elements for each sub-plot); (3) sub-plot image storage in the database (stores the image files and specific information: plot number, horizontal number, coordinates according to the real scene, number of surface elements in each sub-plot). With this knowledge, the sub-plot images can be easily segmented geometrically, at application run-time, assuming approximatively equal widths and heights of the surface elements.

Computer-aided visual investigation of the hydro-dam downstream concrete walls offers the important advantage of an objective and storage-effective identification and quantification of the results, which, on a long-term basis, is an important task to be accomplished by existing software systems for hydro-dams surveillance and monitoring. Of course, such an application requires the use of the human expertise in the visual inspection process, to make possible the correlation of the numerical image analysis results with the qualitative (linguistic) diagnosis/decision provided inherently by the human examiners in the visual inspection tasks. Afterwards, based on the experts collected data, any sub-plot can be analyzed/diagnosed objectively. The results can be provided to both the human examiner and stored in a database at any time, in numerical and visual form, to be used either in the instantaneous decision only or as a reference for further measurements as well. The structure of our system is further described.

3. THE PROPOSED COMPUTER VISION SUPPORT SYSTEM STRUCTURE

The proposed system is thought to offer efficient support to its users, in a two-fold way: to provide them the accuracy, objectivity and repeatability of analysis only possible with a computer based tool, whereas making possible for the expert to "train" the system in making its linguistic decisions, so that to be compliant with the expert inferred knowledge about the deterioration state of the concrete surface. One must take into account that generally it is difficult to visually observe from raw digital images of the concrete surface hydro-dam wall the surface erosion/patterned crack presence, unless some enhancement on suitable features is applied on them.

Therefore a suitable system for our goal should include, *first of all*, an *image/feature enhancement stage* capable of emphasizing and presenting the user an image of the sub-plot and surface elements in which *only the relevant features* for the surface deterioration examination appear. This feature enhancement stage is needed both in the surface deterioration evaluation and in the system training, as the first processing step. Secondly, the system should include the capability of learning rules to associate numerical estimates of the surface deterioration provided by the image analysis module with linguistic qualifiers of the deterioration, compliant with the expert assessment modality. Therefore *a training module* should be designed, to be used in the (potentially needed) training phase of the system. Finally, *a surface evaluation module* to perform the task presented here must be designed. The operation mode of the two modules is illustrated in Fig. 3.

3.1. Feature space for surface deterioration assessment/ visualization

The most discriminative features for our goal, that allow afterwards the quantification of the surface deterioration indicated by its roughness and by the superficial crack patterns possibly present, could be provided by the spatial gradient of the brightness – typically given by a gradient-based edge detector. However, since in practice the edges introduced by joints, shadows, organic deposits, doors and access paths (unwanted in our analysis), have generally larger magnitude than the edges introduced by the concrete surface deterioration (superficial pattern cracks and erosions), a simple edge thresholding (as in typical edge detectors (Vlaicu,1997) would not be enough to distinguish the *desired edge points* vs. all others (that include smooth surfaces but also pixels belonging to objects boundaries). A suitable solution is to apply a three class edge magnitude classification scheme using as data – the edge magnitudes of all the pixels in the currently examined/processed surface element of the sub-plot. We employ here an unsupervised classifier – namely, fuzzy c-means – being very popular in pixel classification/clustering applications (Bezdek,1981). In our previous work on the topic, we concluded that although the first observation about the gradient magnitudes introduced by boundary pixels and by patterned cracks pixels is correct, in practice, the difference between these gradient magnitudes is not large enough to allow their classification with no significant error in the two corresponding classes: region boundaries and pattern cracks or erosion. Therefore we proposed to improve the separation of the two brightness gradient classes by employing, on the gradient magnitude map provided by an e.g. Sobel edge detector, the fuzzy edge enhancement algorithm introduced in (Gordan and Georgakis, 2006). In essence, this enhancement algorithm is a fuzzy logic generalization of the binary two-pass edge thinning (Pitas,2000). Whereas the binary logic version of contour thinning has the effect of producing a contour of one pixel width by removing “redundant information carrier pixels”, the fuzzy logic generalization of the binary rules has the effect of reducing the ambiguity in the gradient magnitudes which leads to better separable edge magnitude classes. Afterwards, on this enhanced edge magnitude map, the performance of the edge magnitude classification using fuzzy c-means and setting the pixels labels according to their maximum membership is significantly better. We call therein: the class of unwanted edges (boundary) pixels, of stronger magnitude – the strong edges class; the class of edges introduced by the concrete surface deterioration – the weak edges class; the class of pixels inside smooth surfaces – the background class.

One issue to be mentioned is that, although it would be computationally more efficient to perform the gradient magnitude computation, fuzzy edge enhancement and classification globally on the set of pixels in the sub-plot, this approach would have the drawback of accounting as weak edge pixels also the ones around the surface elements joints, which should not be accounted for the surface deterioration. Therefore, we prefer to perform the above mentioned processing on each surface element in the subplot individually. An example of the resulting identification of weak edge pixels on a geometrically segmented sub-plot can be seen in Fig. 3.

3.2. Numerical quantifiers of the concrete surface deterioration by erosion and pattern cracks

To be able to assess, even linguistically, the deterioration severity of the concrete surface in each sub-plot of the hydro-dam (globally or as an aggregation of the deterioration severities in the surface elements of the sub-plot) it is not enough to identify and mark accordingly the pixels in the sub-plot image where the signs of erosions and pattern cracks are present, but also some correlation rules between the resulting pattern in the weak edge magnitude map (feature space) and the linguistic qualifiers must be derived. The solution adopted here is a two-step one. *In the first step*, we quantify the deterioration severity in each elementary surface of the sub-plot by a global numerical descriptor, given as the density of point accounting for the concrete deterioration in the elementary surface (i.e. the weak edge pixels). We consider the above introduced mathematical notations for the number of surface elements in the sub-plot. We further denote the set of resulting surface elements sub-images, after the classification of their pixels as belonging most likely to the weak edges class than to any of the other two classes, by the set of $N_H N_V$ matrices $\{\mathbf{B}_i[H_i \times W_i], i=1,2,...,N_H N_V\}$. H_i and W_i represent the height and width of the elementary surface image i in the examined sub-plot. The matrices are thought to represent crisp classification results, although they resulted by a fuzzy classification procedure; thus every value in $\mathbf{B}_i$ is an indicator of whether the pixel on the corresponding spatial position (let’s say line j, column k in the matrix) in the elementary surface i of the sub-plot represents most likely a weak edge point ($\mathbf{B}_i(j,k)=1$) or not ($\mathbf{B}_i(j,k)=0$). Then, the most simple but effective global numerical descriptor of the each surface element i of the sub-plot –

which we decide to employ in our implementation – is *the percent of the values 1 of the crisp classification decisions* from the total pixels in the surface element *i*, denoted d_i:

$$d_i = \frac{\sum_{j=0}^{H_i-1} \sum_{k=0}^{W_i-1} \mathbf{B}_i(j,k)}{H_i W_i} \quad (1)$$

The second step is motivated by the fact that the set of numerical surface deterioration severity descriptors in the sub-plot $\{d_i, i=1,2,...,N_H N_V\}$ are not easily interpretable by the user. First, this is not the way experts would describe the surface deterioration. Secondly, even in severely degraded surface elements, the experiments run give maximum values of d_is somewhere around 0.5, and generally, the mapping of [0;0.5] to a percentage [0;100] deterioration severities scale is not linear. Therefore, a non-linear, expert learned mapping must be derived from the global numerical descriptors d_i space to a deterioration severity description in the sub-plot elements compliant with the human experts' reasoning/expression. This is achieved in the training module of our system, described below.

3.3. Operation in the training phase

The training phase of the proposed system is thought as strictly necessary only once per hydro-dam application framework and database population with meaningful images, to derive a meaningful mapping of the image analysis numerical results at sub-plot level to linguistic qualifiers of the concrete deterioration in the sub-plot image. This mapping is stored as default in the database of the integrated system installed for the current hydro-dam inspection. However, considering the possible changes during time of the appearance of the concrete surface in general and of the imaging conditions, the possibility to re-train the mapping parameters has to be provided as an option to the user, if it is considered to be incompliant to the human linguistic assessment of the surface deterioration severity, provided that the human will not only examine the raw sub-plot surface image, but also the enhanced weak edges map, to emphasize the erosions and superficial pattern cracks that might be hard to observe without image enhancement aid. The mapping rules should be "learned" from human experts' opinions, by gathering the human selections (from a predefined list of options) for the severity of the deterioration in a visual examination process of the original and weak edge maps of the surface elements in several sub-plots and correlating them with the numerical extracted descriptors.

Since humans naturally describe by words the visual quality of an examined scene, the suitable association is in the form of *numbers-to - linguistic values*, to which plausibility can be added in order to give a more precise "categorization" of the deterioration state of a given surface element in the sub-plot. A powerful mathematical framework for easily mapping numerical to linguistic values is the fuzzy sets theory. In the fuzzy set theory, each linguistic value denotes a fuzzy set, completely described mathematically through its membership function. The membership functions itself, defined over the universe of discourse of the numerical descriptors of concrete surface element deteriorations d_i, namely – [0;1], is typically a parametric mapping, with values in the set of membership degrees [0;1], showing the degree in which a value d_i can be linguistically defined by the corresponding linguistic value. Several choices can be made for the analytical form of the fuzzy sets membership functions. The Gaussian and combinations of Gaussians are ones of the most commons. Human expert gathered information are used to derive the parameters of the fuzzy membership functions. We chose to use Gaussian shaped membership functions since their parameters can be directly estimated from the mean and standard deviation of the acquired training data. As linguistic values of the severity of the superficial deterioration of the concrete layer hydro-dam downstream wall, users agree on a set of the following four terms: *Not deteriorated*, *Slightly deteriorated*, *Rather deteriorated* and *Very deteriorated* – represented each through a fuzzy set. To ensure a complete coverage of the universe of discourse, the two extreme fuzzy sets describing the linguistic concepts *Not deteriorated* and *Very deteriorated* are chosen to give a membership of 1 to the extremes of the universe of discourse (non-symmetrical). The four membership functions are denoted: *NDet*: $[0;1]\rightarrow[0;1]$, *SDet*: $[0;1]\rightarrow[0;1]$, *RDet*: $[0;1]\rightarrow[0;1]$, *VDet*: $[0;1]\rightarrow[0;1]$, given by:

$$NDet(d_i) = \begin{cases} 1, & d_i < \mu_{NDet} \\ e^{-\frac{(d_i - \mu_{NDet})^2}{2 \cdot sd_{NDet}^2}}, & otherwise \end{cases},$$

$$SDet(d_i) = e^{-\frac{(d_i - \mu_{SDet})^2}{2 \cdot sd_{SDet}^2}}, RDet(d_i) = e^{-\frac{(d_i - \mu_{RDet})^2}{2 \cdot sd_{RDet}^2}},$$

$$VDet(d_i) = \begin{cases} e^{-\frac{(d_i - \mu_{VDet})^2}{2 \cdot sd_{VDet}^2}}, & d_i < \mu_{VDet} \\ 1, & otherwise \end{cases}. \quad (2)$$

The procedure for finding the parameters of the fuzzy sets (mean and standard deviation) is the following. For a sub-plot image at his choice, the examiner is presented with the surface elements segmented image (marked by a non-rectangular grid over-imposed on the sub-plot image) and simultaneously with its weak edge magnitude map (as in Fig. 3.a)). When clicking a particular surface element *i*, a detailed view in the visible domain and its weak edge magnitude map are shown to the user, who is then prompted to check one of the four linguistic qualifiers of the deterioration severity of the surface in the element *i*, or at most two neighbor qualifiers, if its deterioration is considered to be "on the border" of two neighbor classes. The linguistic categorization allows for the element's deterioration numerical descriptor d_i to be assigned to the class (or at most two classes) specified by the user. Thus in the end of the examination, a set of training data in the four linguistic values categories is obtained. Let N_k be the number of data gathered in the category *k*, $k \in \{NDet, SDet, RDet, VDet\}$, $N_k \neq 0$, the data in the category *k* – the set $\{d_{l,k}\}, l = 1,2,...,N_k$. The mean μ_k and standard deviation sd_k of the data can be used as estimates of the parameters of the Gaussian membership functions.

3.4. Operation in the evaluation phase

The evaluation module is called from the main visual inspections sub-system of the dam surveillance decision support tool application. Its operation is as follows: first, it loads the current sub-plot image from the database. Along with the image file, the information about the sub-plot position and geometry, i.e., N_H and N_V) is also retrieved. Using this information, the grid lines whose boundaries segment the surface elements are derived, providing the sub-plot image description as a set of surface element images, $\{\mathbf{U}_i[H_i \times W_i]\}$. Each surface element *i* is further subject to the processing described in Sub-sections 3.1. and 3.2 above. The feature extraction in each surface element *i* ends with the computation of the global numerical descriptors d_i, stored in a vector $\mathbf{d}[N_H N_V \times 1]$, specific to the sub-plot.

In the subsequent phase, the fuzzy sets membership functions *NDet*, *SDet*, *RDet* and *VDet* previously "learned" and stored in the database by the training module, are used on the examined data, to assess the memberships of all the values in **d** to the four linguistic categories. An aggregated measure of concrete surface deterioration severity at the sub-plot level can be estimated by the average degree of matching the four linguistic qualifiers by the surface elements in the subplot, which provides an indicator of the most likely linguistic value of the severity of surface deterioration at sub-plot level:

$$p_q = \frac{\sum_{i=1}^{N_H N_V} qDet(d_i)}{N_H N_V}, \quad q \in \{N, S, R, V\}. \quad (3)$$

The terms in Equation (3) above can be interpreted as aggregated sub-plot likelihoods of deterioration state. They are displayed as values and bar graphs, as illustrated in Fig. 3.b).

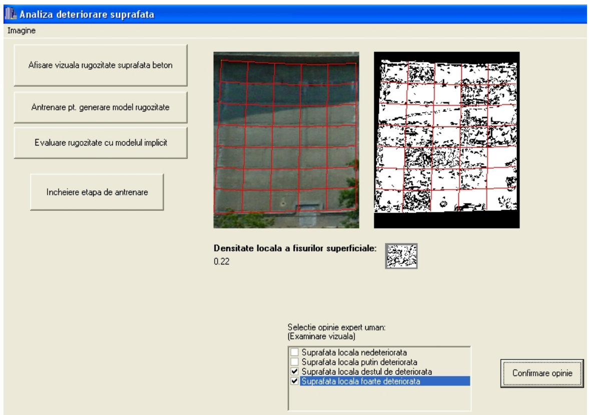
In the purpose of helping the user in the assessment of the global severity of concrete surface deterioration in the sub-plot, one more display modality has been implemented as a result of surface deterioration diagnosis module – in the form of a color sub-plot map, obtained by pseudo-coloring the individual surface elements according to their most likely severity category, mapped to a color legend. In designing the color legend, we took into account that each linguistic descriptor of the deterioration severity should be compliant with the color coding of normal to critical situations encountered by the humans in other common applications. As such, we chose the colors in the legend to be: green (not deteriorated), yellow (slightly deteriorated), orange (rather deteriorated) and red (for very deteriorated).

The severity degree of the surface deterioration color map is generated as follows. The surface elements in the sub-plot image are rendered in either the color of the most likely class they belong to, or, if two classes have not clearly disimilar likelihoods (in the scheme implemented here, this means, if the two most likely classes have differences in likelihoods less than 0.5), the color of the element is "computed" as a weighted average (in the HLS domain, on the hue component H, the saturation S and luma L being considered the same in the map) of these two classes, with the weights proportional to these likelihoods.

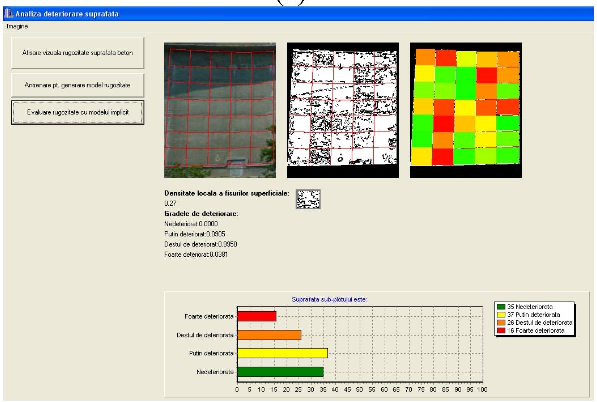
4. IMPLEMENTATION AND RESULTS

To validate the proposed computer vision support system performance in assessing the severity of the concrete surface deterioration on existing dams, we implemented it as software module and integrated it within the complex system described in Section 2. The system's interface (both in the learning and evaluation phase) can be seen in Fig. 3. Experiments were run on a set of 20 images of different sub-plots, taken from the downstream walls of the Tarnita dam on the Somes River, previously stored in the database. The parameters of the fuzzy sets used to correlate the linguistic description of the deterioration severity of the surface with its corresponding numerical quantifiers were derived from other 10 sub-plot images, from the database.

Since the purpose of our computer vision tool is to provide effective support to the user assessment of the deterioration severity on each sub-plot, its evaluation should be done using as reference the expert opinion on the same matter, having available the same sub-plot image examined either globally or on the level of its surface elements, with edge enhancement available. In this respect, although so far we had only access to a few users's feedback, on the 20 sub-plot images considered, their opinion was generally compliant to the overall evaluation of the deterioration given by our software. In some cases the deterioration was considered less severe by the humans than by the software. This means a higher false alarm of the system than the human expert, but this is not as worrying as missed true severe deteriorations. An example of operation of our system is given in Fig. 3. The partial results and users' feedback can be considered promising for the use of this tool in the assisted visual assessment of the superficial deterioration of the dam wall.



(a)



(b)

Fig. 3. An example sub-plot analysis and its use in: (a) the training phase, to derive fuzzy sets parameters; (b) the evaluation phase, to asses the concrete surface deterioration severity

5. CONCLUSIONS

We proposed, designed and implemented a novel hydro-dam surface deterioration assessment tool, integrated in a complex system for hydro-dams safety assessment and monitoring. This tool integrates image analysis and linguistic assessment techniques, complemented with pseudo-coloring, to serve as better possible the assisted examination of concrete surface deterioration required in hydro-dams visual inspections. The use of objective measurements combined with the representation of the results in a way compliant to the user assessment of image analysis results (by color maps and through linguistic qualifiers) offers effective support to human observers and the objectivity and repeatability of the results needed for keeping track on the surface deterioration in time. In the future, this computer-aided assessment tool, integrated in the database application for hydro-dams monitoring, will be used for generating automatic visual reports and possibly integrated with other modalities of examination.

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