A Novel Fuzzy Edge Detection and Classification Scheme to Aid Hydro-dams Surface Examination

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Abstract

The visual examination of downstream faces of hydro - dams is an important component in their monitoring. Few computer vision algorithms exist for this task. Some of them aim to detect and evaluate concrete cracks using edge detection. Other problems can also affect hydro-dams, as roughness, scratches, and can lead in time to surface deterioration. These are not currently reliably addressed by image analysis. The proposed fuzzy edge detection and classification scheme can assist the human expert in the visual inspection for crack examination and non-critical surface faults. To differentiate between them we use a fuzzy c-means classifier on the edge strengths, which are found using Sobel edge detection and enhanced through a fuzzy algorithm. The scheme is validated through experiments on different images. The resulting edge maps emphasize superficial faults or cracks, depending on the user's selection, providing more accurate results than classical edge detection.

1 Introduction

Surveillance of hydro-dams represents a serious environmental problem. The consequences of their failures can dramatically affect the environment and humans. 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 [1, 2, 3]. Among the important aspects monitored in a visual inspection process of a hydro-dam, of particular interest is the examination of the down-stream hydro-dam surface, to detect and measure evolving cracks, but also superficial irregularities (scratches, roughness), which, although not critical, can indicate a surface more prone to structural faults [4]. One of the simplest way to describe the roughness and possible cracks on a surface is through edge detection. Edges are simple and reliable indicators of both texture and cracks [5]; however, usually a simple edge detector will not do for the description of the hydro-dam's surface, neither locally nor globally applied, since edges not corresponding to cracks nor to surface scratches, can appear in the image. A more sophisticated edge detection scheme would be needed, able to differentiate between the different types of edges, allowing to separate accurately the edges of interest from all the others. Such an approach is presented in this paper and verified for the analysis of a plot from the downstream wall of a hydro-dam in Romania on the Somes river. If one aims to analyze the surface just for superficial faults, the small magnitude edges should be the only present in the edge image, whereas to examine major faults as cracks, they have to be "filtered out" from the image. A good strategy is a classification of edges according to their strengths into strong edges, weak edges and no edges (uniform surface). Such a strategy is employed in the proposed scheme, using a fuzzy c-means classifier on fuzzy enhanced edge magnitudes. A related approach concerning fuzzy classification of edges for image analysis is reported in [6]. However in the proposed method we also enhance the gradient magnitudes prior to classification [7] to emphasize the weak edges and thus make more visible also the superficial faults. The algorithm behind the proposed scheme, some experimental results and the conclusions about the performance of our approach are presented in the following.

2 The proposed scheme

Since the goal of our work is to develop a computer vision tool to assist the human operator in detecting and evaluating surface irregularities on the downstream face of a hydro-dam, the proposed algorithm is application-oriented. We do not intend to develop a general, universal surface descriptor based on edge information, but rather an algorithm to work well in the proposed specific task.

2.1 Problem description

The concrete down-stream wall surface of a dam to be examined is composed from plots. Each plot contains elementary "plates", the so-called sub-plots, stick together in the plot structure. When one visually examines the surface of the hydro-dam wall, the state of each elementary sub-plot has to be examined for scratches / roughness and for possible cracks. Examining the plot image at sub-plot level partially compensates for the variable lighting conditions.

(1) The first type of surface irregularities include scratches and abnormal roughness. If only these would be present on the sub-plot surface, assuming uniform lighting conditions at sub-plot level, any simple edge detector would produce an edge magnitude map able to accurately describe these irregularities present on the surface.

(2) A second type of elements that will produce lighting variations can be present on the sub-plot surface, that is, cracks. This second category will generally produce larger edge magnitudes than the first. The proposed approach classifies the resulting sub-plot edge map into weak edges and strong edges.

2.2 Description of the proposed approach

The proposed edge detection and classification - based scheme for hydro-dam surface characterization implies the following stages.

1. The preprocessing stage has the task of segmenting the plot surface into the sub-plot patches to be analyzed; their number depends on the particular hydro-dam and is assumed to be known a-priori. Thus we know a-priori how many horizontal sub-plot slices compose the plot (let us denote this number by N_{horiz}) and the number of sub - plots in each slice (let us denote this number by N_{vert}). Therefore as a result of the segmentation, a set of $N_{horiz} \cdot N_{vert}$ approximately rectangular region of interest to be analyzed is obtained, as illustrated in Fig. 1(a), which approximate the real sub-plots, by considering a plot delineation given by the user and dividing it horizontally and vertically into equally spaced slices. We describe each resulting region of interest by a gray scale image X_i of size $H_i \times W_i$, $i = 1, 2, \dots, N_{horiz} \cdot N_{vert}$. The regions of interest delineation also accounts for the curvature of the plot, horizontally oriented, by considering equal intervals on each vertical line from the top of the plot contour to its bottom. From this point forward, all the processing is performed at the region of interest level.

2. The Sobel edge detection stage computes the vertical and horizontal gradient images, G_{xi} and G_{yi}, $i = 1, 2, \dots, N_{horiz} \cdot N_{vert}$, by convolution with the vertical and horizontal Sobel masks. From the two convolution results we obtain the gradient magnitude image matrices. The result is a first set of edge magnitude maps $G_i[W_i \times H_i]$ of all regions of interest, $i = 1, 2, \dots, N_{horiz} \cdot N_{vert}$.

3. The fuzzy edge enhancement stage receives on its input the gradient magnitude maps $G_i[W_i \times H_i]$, $i = 1, 2, \dots, N_{horiz} \cdot N_{vert}$. Since the separability of the magnitudes into strong edges, weak edges and background is rather poor, we cannot rely simply on this edge map to perform the edge classification. Therefore we enhance the separability of the edges into weak, strong and at all (background) through an algorithm able to emphasize their attributes and to improve the histogram's separability (in the meaning of creating more clear local maxima and minima). Such a goal can be achieved by a previously developed fuzzy algorithm, which we will call here *the fuzzy edge enhancement algorithm* [7]. This algorithm is a fuzzy logic generalization of the binary logic two - pass edge thinning algorithm presented in [8]. The algorithm scales each edge magnitude $G_i[k][l]$ in the range $[0; 1]$. The resulting maps g_i, $i = 1, 2, \dots, N_{horiz} \cdot N_{vert}$ represent *the possibilities* for the corresponding pixels to be edges. These possibilities are processed in two passes through the image. In each pass, a fuzzy if - then rule base of 34 rules is evaluated using the Mamdani fuzzy inference mechanism to derive the resulting possibility for each pixel to be edge, $g_{i,enh}[k][l]$, $k = 1, 2, \dots, H_i, l = 1, 2, \dots, W_i,$, $i = 1, 2, \dots, N_{horiz} \cdot N_{vert}$. The two rule bases result from generalizing the boolean logic rules of the binary logic edge thinning algorithm [8]. The generalization consists in relaxing the concept of edge by considering, instead of crisp values zero (background) and one (edge) for $g_i[k][l]$, any values in $[0; 1]$. Thus each of the boolean logic rules represented above is explicitly written considering nine antecedents (which correspond to the possibilities of $g_i[k+p][l+q]$, $p = -1, 0, 1$ and $q = -1, 0, 1$, to represent edges) and one consequent, as a set of 34 logic rules. The approach emphasizes weak edges and preserves only the significant strong edges, allowing to identify both categories in the image.

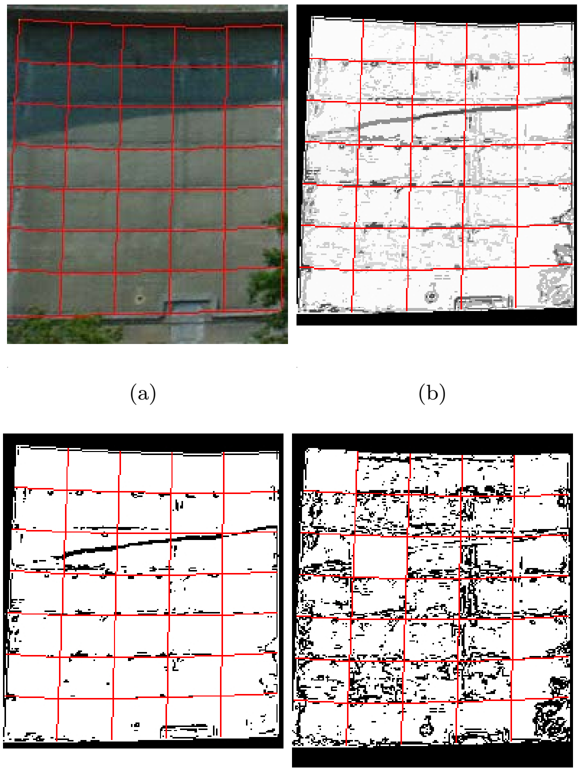
4. The fuzzy c-means edge classifier is finally applied on each fuzzy enhanced gradient magnitude map $g_{i,enh}$, $i = 1, 2, \ldots, N_{horiz} \cdot N_{vert}$. The description of the fuzzy c-means clustering algorithm can be found in [9]. Since we aim to differentiate three types of edges, we apply the fuzzy c-means algorithm for $C = 3$ classes, using the standard Euclidean distance measure and the parameter $m = 2$. The convergence error ϵ was set to 0.1%. After the convergence of the fuzzy c-means classification procedure, the three class centroids are obtained, let us denote them as $v_{i,1}$ for the strong edges, $v_{i,2}$ for the weak edges and $v_{i,3}$ for the background. Also the final partition matrix is obtained, denoted by $U_i[3 \times W_i \cdot H_i]$, containing the fuzzy membership degrees of the pixels in the current processed magnitude map i, $i = 1, 2, \ldots, N_{horiz} \cdot N_{vert}$, to the three classes, namely: strong edge class, weak edge class and no edge class (background). The three classes are decided based on the magnitude of the resulting centroids: the largest centroid value will correspond to the strong edge class, the smallest to the background class and the one in between - to the weak edge class. Then each pixel is assigned in a crisp manner to the class where it has the maximum membership. As a result, two edge maps represented as binary matrices, $V_{i,s}[W_i \times H_i]$ (strong edges) and $V_{i,w}[W_i \times H_i]$ (weak edges), $i = 1, 2, \ldots, N_{horiz} \cdot N_{vert}$ are built for the current slice i, as follows. The pixels in the matrix are set to black (gray level 0) if they represent edge points of the corresponding strength, or to white otherwise (gray level 255).

3 Experimental results

In order to validate the results of the proposed fuzzy edge detection and classification scheme, we implemented it software in C++ as a Windows application and we applied it on several different test images.

The test images considered are: five test images representing, each, a plot from the downstream face of the hydro-dam; three test images representing portions of a building's wall; three test images representing portions of a road, with/without cracks; an underwater image of the dam wall (from its upstream face).

An example from the first and the second category is presented below, in Fig. 1 and 2. One can see:
(1) The original image considered, with its segmentation into rectangular individual regions according to the preprocessing stage (which in case of a downstream face of a hydro - dam, corresponds to a sub - plot plate each) (Fig. 1(a) and Fig. 2(a)).
(2) The result of the Sobel edge detection and fuzzy edge enhancement in each individual rectangular region of interest (Fig. 1(b) and Fig. 2(b)).
(3) The result of the edge classification, in the form of: strong edges map (Fig. 1(c) and Fig. 2(c)) and weak edges map (Fig. 1(d) and Fig. 2(d)).



(a) (b)

(c) (d)

Figure 1: a) The original image; b) Sobel edge detection and fuzzy edge enhancement; c) The strong edges map, and d) The weak edges map

For the time being, the evaluation of the results is performed visually, not quantitatively. One can notice from the figures above the ability of the proposed scheme to identify correctly in most of the cases the large luminance variations (i.e. the strong edges) as well as its ability to emphasize the roughness and scratches of the surfaces, not always obvious in the visual examination by humans. We may notice from the examination of these images that false alarms can appear in several regions (either in the form of strong edges or a too large weak edge density). However as long as this system is not designed to perform an automatic surface diagnosis, but rather as a tool to assist the human

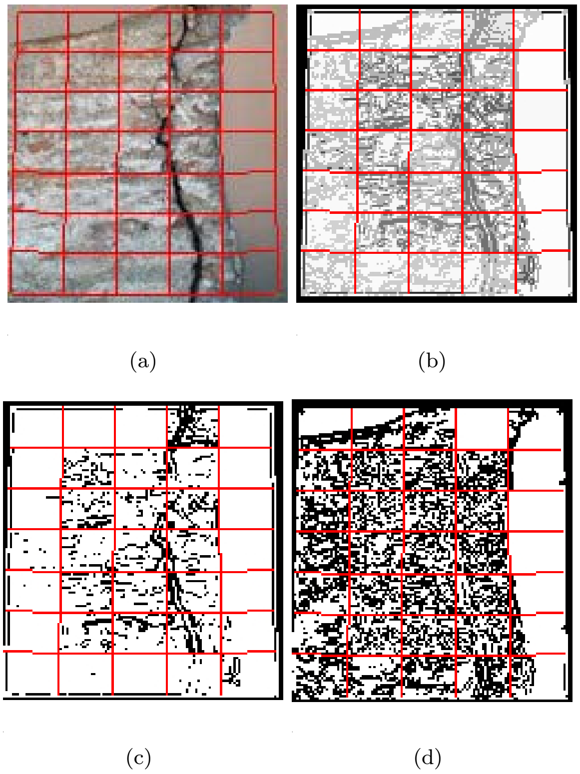


Figure 2: a) The original. b) Sobel edge detection and fuzzy edge enhancement. c) The strong edges map. d) The weak edges map

operator in the examination of these surfaces, we prefer a false alarm than missed faults.

Due to the application of the fuzzy c-means classification on a local basis, the computational complexity of the proposed approach is not significant. The processing time per plot image (200×240 pixels) is on the order of seconds. One must mention here that the computational complexity of the fuzzy c-means classifier is the most significant in the proposed procedure and it scales with the number of data to be classified.

4 Conclusions

In this paper we introduced a novel approach to the characterization of the surface of a hydro-dam, specifically designed to assist the user in the visual examination of this surface at plot and sub-plot level, with the aim at finding if the surface has minor superficial faults (as scratches, pronounced roughness) - difficult to perceive directly on the acquired images - or, as opposite, if it presents significant faults as cracks or major deterioration. The functionality of the proposed scheme is validated on test images. The results are according to the human expectations for the task addressed. One drawback is the false alarm. Reducing it will make the object of our future work, as well as employing this scheme into an expert system able to linguistically and numerically assess the surface's state.

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