The concept of a competitive step and roof edge detector

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Abstract. A concept of using data obtained as a side effect by a new version of the competitive filter to detect step and roof edges in an image is described. Promising properties of the new detector presented with 1D examples indicate that the 2D extension which is now being developed could become a valuable tool in analysing images with piecewise linear brightness function corrupted with noise.

Key words: edge detector, step edge, roof edge, competitive filter.

1. Introduction

The methods of detecting step edges are so numerous that to make an adequate overview would be a target on its own. Some detectors became exceptionally widely used, which may indicate the consensus on their generality. Among them there is the gradient-based Sobel detector [1], the second derivative zero-crossing detector of Marr and Hildreth [2], and the detector developed by Deriche [6] according to the Canny criteria [3].

If the roof edges are considered, however, the situation is different. The number of publications is smaller, and no single concept seems to be far in front of the competition. It is not my objective to summarize all the related work done hitherto, so I shall cite only some of the references which seem informative.

Blake and Zisserman in [5] have developed their concept of approximation filters based on mechanical analogies, which detect edges while removing noise. The membrane filter detects the function discontinuity (step edge), and the plate one finds the first derivative discontinuity (roof edge). Good mathematical foundation and excellent behaviour for noisy signals are obtained, at the cost of complexity and low speed of iteration algorithms (cf. [11]).

A relatively efficient roof edge detector was proposed by Pajdla and Hlaváč [10]. It comes back to the concept of fitting edge model to the image, like in [4], but now the initially found edge direction information makes it possible to reduce the problem dimension to one.

Kuriański [12] was one of a large number of researchers who have investigated a detector based on the Canny principles. The main problems with this detector seemed to be how to extend the Canny's 1D concept [3] to 2D. The derived detector appeared to find well only very "sharp" roofs, which corresponded to lines.

It can be safely said that the problem of finding the roof edges is still far from being satisfactorily and efficiently solvable. Therefore, there is still room for proposing new methods.

In this paper a method of simultaneously filtering an image and finding step and roof edges in it will be described. The idea of the filter which has served as a basis of the proposed concept has been developed by Niedźwiecki, Sethares and Suchomski in [9, 13], where the filter was denoted as the *competitive filter*.

The design of the competitive filter makes it possible to avoid filtering "across" an edge. In the approach presented here the information on the presence of an edge, which is available as a side-effect in the competitive filter, is used explicitly to obtain the *competitive detector of step and roof edges*.

At the present stage a 1D version of the detector will be described in detail, and some ideas of how it can be extended to 2D will be given. The work on the 2D version of the detector is now under way. Experiments with artificial as well as natural 1D images will be presented.

2. The concept of the Competitive Edge Detector in 1D

Let us briefly remind the main idea of a 1D version of a competitive filter according to [13]. The aim was to find a time sequence $y(t)$ given the measurements $z(t)$, under the assumption that $z(t) = y(t) + n(t)$, where $n(t)$ was the measurement noise. Time t was considered as discrete, and the whole measurements sequence as given.

The main idea was to run two predictors on the data surrounding the considered point t_0. The first one was running towards future, and yielded $\hat{y}_-(t_0)$ as an estimate of $y(t_0)$, basing on observations from the past with respect to t_0. The second one, running towards past, yielded $\hat{y}_+(t_0)$, basing on the future w.r.t. t_0. As the output of the filter the result of that predictor was chosen which had a lower error index, that is, the one which performed better in a number of its recent predictions in the sense of square mean of prediction errors.

Let us illustrate a simplified competitive filter [13], in which as a predicted value the average of the nearest λ (*scale* of the filter) measurements is taken. (Fig. 1). As the error index the mean square fitting errors can be used. In the figure, the future predictor wins.

In the following we shall consider spatial distributions of brightness functions $I(x)$ rather than time sequences, so the notations will change accordingly.

Let us now assume that the fitted functions is affine rather than constant. The method of fitting is arbitrary; at the first thought we would take the least mean squares (LMS) fitting, while for example the least median of squares [8, 7] could probably be a better solution. LMS fitting will be used throughout the paper. Now, the filtered value will be

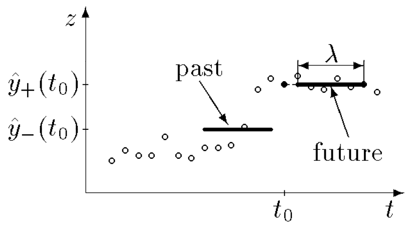

Fig. 1. Averaging competitive filter. λ: scale; $\hat{y}_-(t_0)$, $\hat{y}_+(t_0)$: outputs from predictors working from past and future towards t_0.

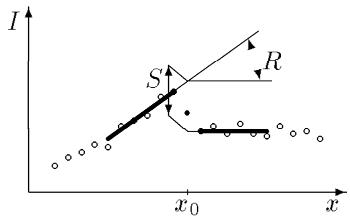

Fig. 2. 1D step and roof edge. S, R: step and roof intensities at x_0.

the extrapolation to the considered pixel x_0 of that affine function which has a better fit.

The fact that an affine function has been chosen in fitting implies that the filter/detector is supposed to work the best with images in which brightness is close to piecewise linear.

Let us examine Fig. 2. The information on the fitted affine functions contains the information on the step edge intensity at x_0. Namely, this is the difference in the predicted values S, if a pixel x_0 is located at a step edge. If there is a roof edge at that pixel, the angle R can be considered as the roof edge intensity.

In the case of our edge detector, unlike in the case of other detectors, it is not guaranteed that the edge intensity will be maximum at the edge location. To see how the precise location of the edge can be found we shall first consider the examples in the next section.

3. Edge location

We shall consider a one-dimensional artificial image of a combined step-roof edge (Fig. 3), in a noiseless and a noisy version with additive Gaussian noise ($\sigma = 10$).

Let us examine the three graphs in Fig. 3 a, b and c, which show the image brightness data and the intensites of the step and roof edge. The scale for each filter is 10. The step intensity has a maximum at the actual step ($x = 29, 30$), but it also has two minima in the neighbourhood. For the roof edge intensity the situation is similar. This makes it impossible to either detect or locate edges merely on the basis of edge intensity data.

Let us consider the mean square fitting errors of lines used to produce the edge intensity measures in Fig. 3 d. The errors for the filter operating on the *past* with respect to the considered data point are denoted E_-, and the errors for the *future* – E_+.

The first observation concerning the errors around the edge is that *before* the edge

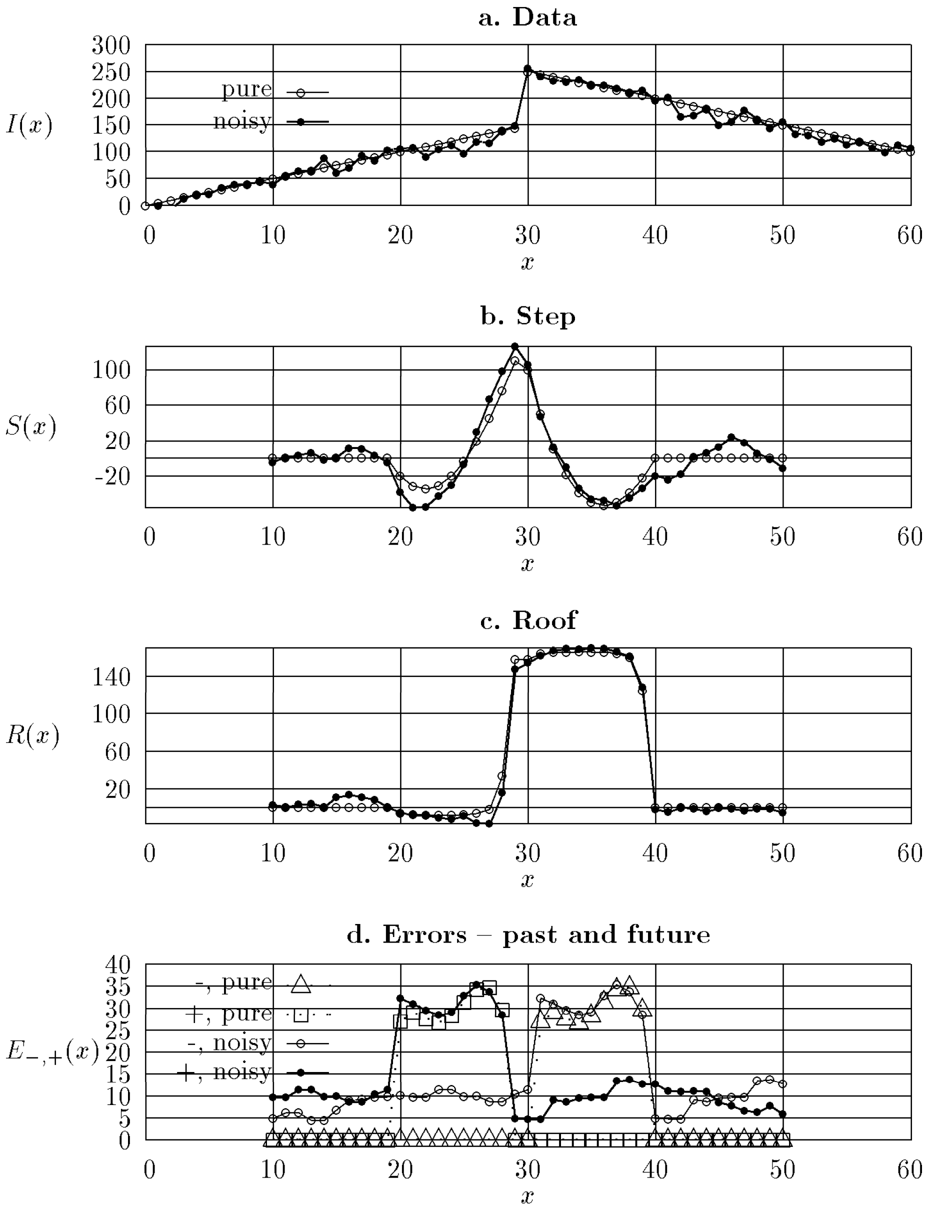

Fig. 3. Artificial joint step and roof edge with and without noise.

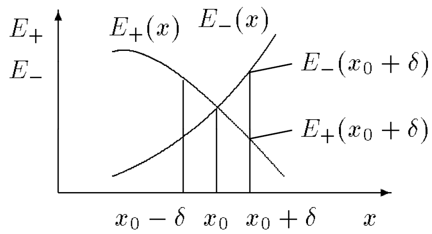

Fig. 4. Illustration of the edge existence measure (2) based on the crossing of graphs of fitting errors E_- and E_+ around the point x_0.

(in the past) the future error E_+ is larger than the past one E_-, and *behind* the edge – E_- is larger than E_+. In other words, the graphs of errors *cross* each other. It is proposed to build the necessary condition for the existence of an edge at a specified data point on this observation. The above remarks on error distribution hold also for pure step and roof edges, not shown here.

Let us introduce the measure of the *quality of crossing*. This measure will be considered as the measure of fulfillment of the edge existence condition at a specified point.

First let us introduce the relative measure $L(y_1, y_2)$ of how much y_1 is larger than y_2. The square errors are nonnegative, so $y_1 \geq 0$, $y_2 \geq 0$.

$$L(y_1, y_2) = \begin{cases} -1 & \text{if} \quad y_1 < y_2 \; , \\ 1 & \text{if} \quad y_1 \geq y_2 \text{ and } y_1 = 0 \;\; (\text{then also } y_2 = 0) \; , \\ \frac{y_1 - y_2}{y_1} & \text{if} \quad y_1 \geq y_2 \text{ and } y_1 > 0 \; . \end{cases} \tag{1}$$

The proposed edge existence measure can be defined as (Fig. 4)

$$C_\delta(x) = \min \left\{ \begin{array}{ll} L[E_-(x+\delta), E_+(x+\delta)], & L[E_+(x-\delta), E_-(x-\delta)], \\ L[E_-(x+\delta), E_-(x-\delta)], & L[E_+(x-\delta), E_+(x+\delta)] \end{array} \right\} , \tag{2}$$

where δ is a distance parameter. If we set $\delta = 0.5$ we shall obtain the crossing point of error graphs *between* the measurement points. The nearest point should then be taken as the edge location.

The edge existence measure can be combined with the edge intensity to obtain the edge detector which yields narrow, one pixel-wide edges. In the simpliest case the two measures should be thresholded. In the above considered example with noise the condition $C_{0.5}(x) \geq 0$ is fulfilled at $x = 16$, $x = 29$ and at $x = 45$. The edges have been found correctly.

4. Example

An example of results of the proposed detector obtained for a row of a natural image (Fig. 7) are shown in Figs. 5 and 6. The image processed is a view of a ferrite core with

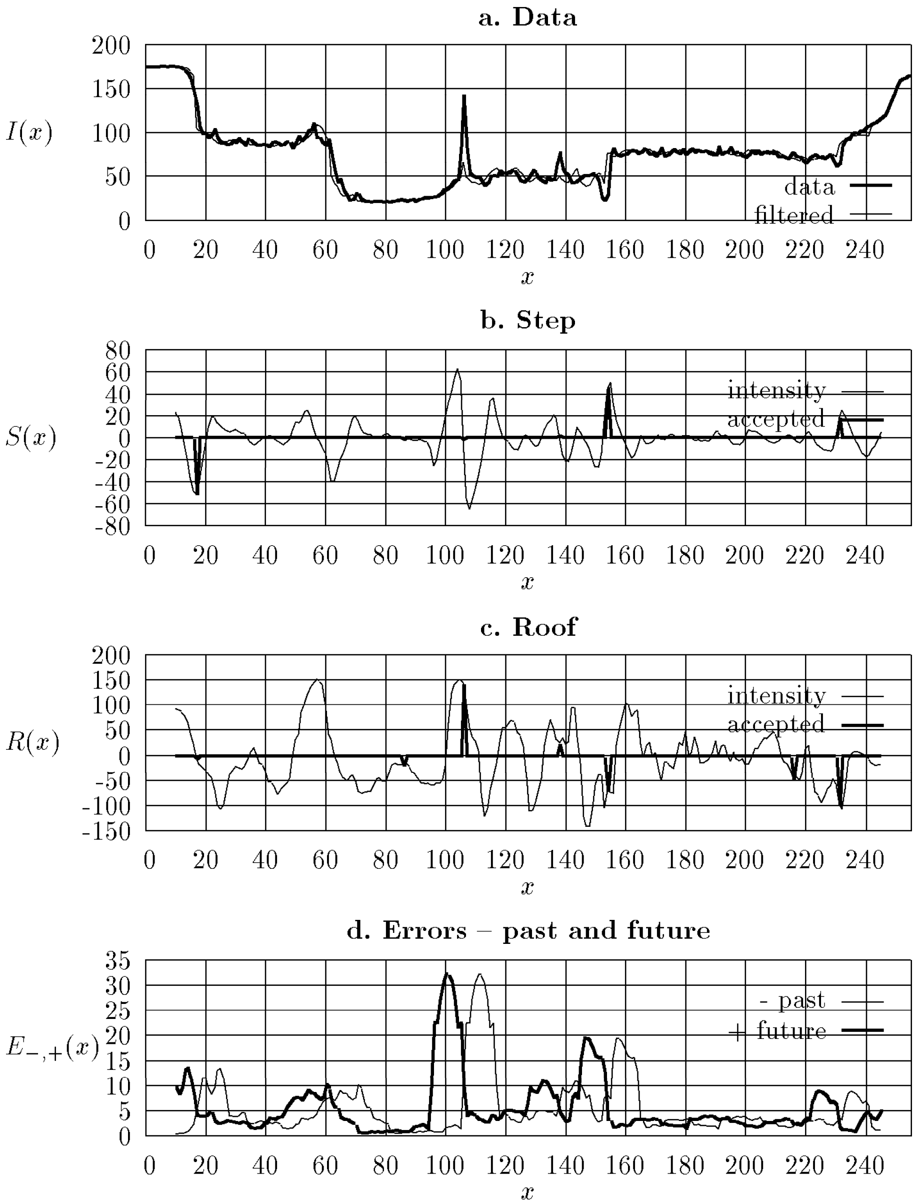

Fig. 5. Results for scale $\lambda = 10$. Slope at $x \in (60, 68)$ not considered as a step.

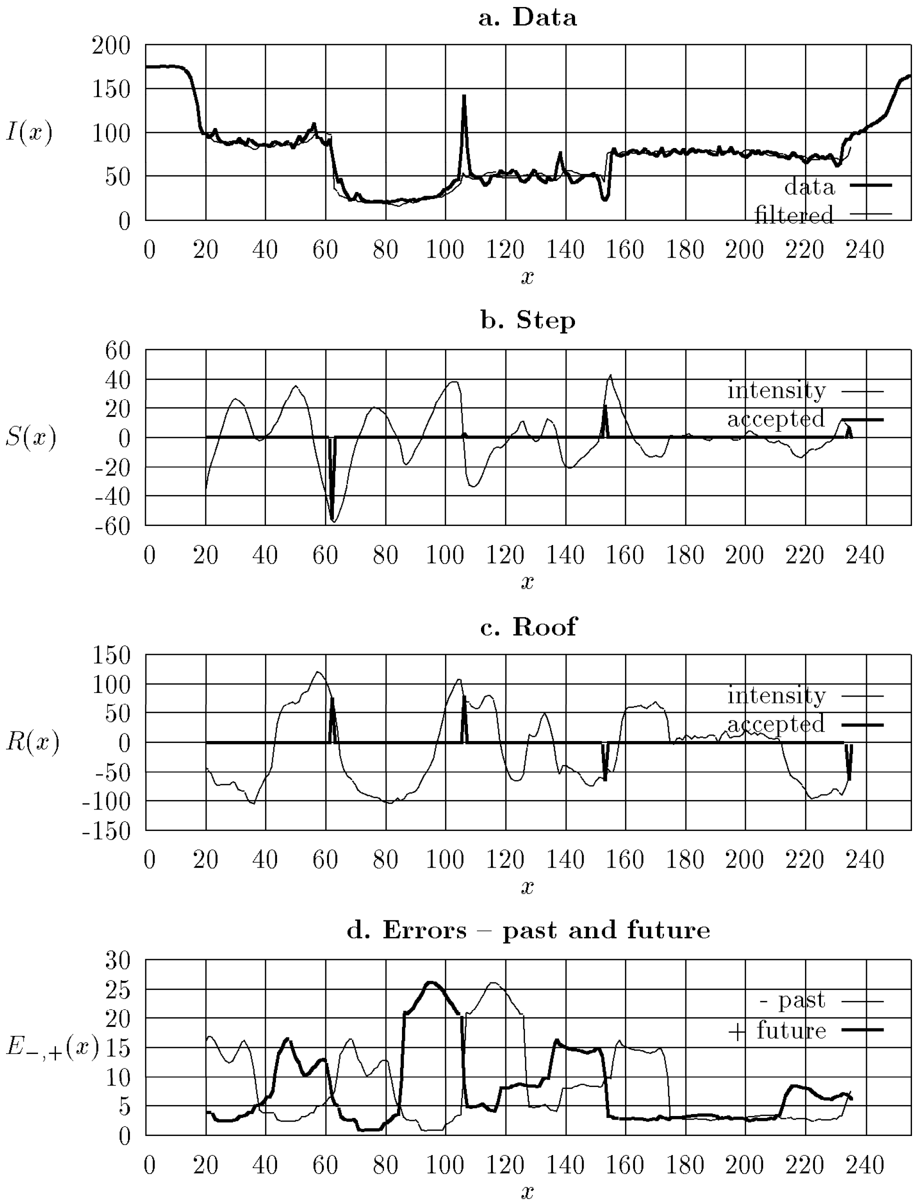

Fig. 6. Results for scale $\lambda = 20$. All significant edges found correctly.

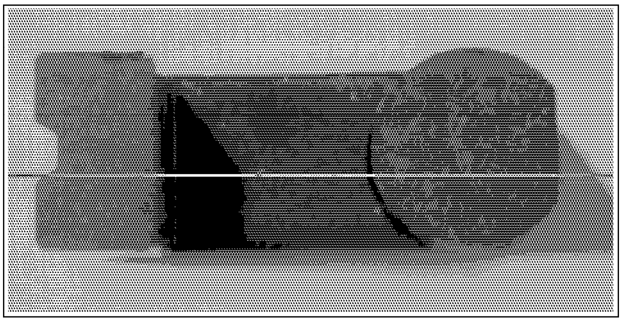

Fig. 7. The analysed row of the picture.

an imperfection on the surface. Its brightness function fulfills the condition of piecewise affinity quite well. The edge existence condition is again $C_{0.5}(x) \geq 0$, according to (2).

The presented graphs indicate that the results produced by the detector are in good conformity with expectations. Large scales should be used if soft edges are to be detected as steps. It should be stressed that the defined detector uses gradient information to find the strength of the roof edges rather than to detect steps. Steep but extended slopes are not detected.

5. Possible extensions to 2D

The concept presented in the previous sections can be extended to two dimensions in numerous ways. Two of them will be outlined here.

Let us consider the neighbourhood of a pixel in the form of eight sets of pixels lying on eight lines, as shown in Fig. 8. Let us call the pixels lying on each line a branch. Each pair of opposite branches constitutes a 1D filter. As the output of the 2D filter the value coming from that 1D filter can be taken for which the fitting accuracy is the best. As the output edge intensities the intensities found by that 1D filter can be chosen for which the edge existence measure (2) is the largest.

In Fig. 9 instead of linear branches a set of possible square neighbouring regions for a pixel are shown. Let us call them leaves. Two leaves form a filter: not only the opposite leaves, like L_1 and L_3, but also the neighbouring ones, like L_1 and L_2. This is vital for proper behaviour at edge joints. In this version of the detector the same rules as in that with 1D branches are applied.

The advantage of leaves with respect to branches is twofold: better noise resistance can be obtained as more pixels are considered in each filter, and edge orientation can be revealed by taking into account the orientation of the gap between the leaves of

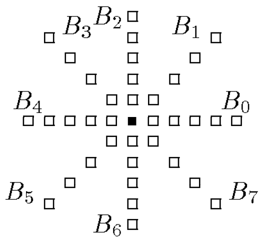

Fig. 8. A pixel of a 2D image and its neighbourhood consisting of eight branches $B_0 - B_7$ (see text).

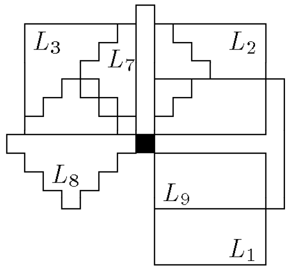

Fig. 9. A pixel of a 2D image and examples of its possible square leaves (see text).

the pair which gives the best edge existence measure[1]. A clear disadvantage is larger computational complexity of 2D fitting.

It should be noted that the remarks on the possibility of carrying out the calculations in an efficient way, made in [13], hold also in the case of the above proposed 2D detectors. For example, each of the leaves shown in Fig. 9 can be used for four pixels (lying in four positions around the leaf). Also the intermediate results used in calculating the parameters of the affine approximations of the brightness function within the leaf can be updated by adding/subtracting the shares only for those pixels which enter/leave the particular leaf as it moves across the image. Nevertheless, the complexity of the 2D algorithm can be substantial, and large memory will be needed to store data for multiple use.

6. Conclusion

The edge detector based on the concept of a *competitive filter* has been proposed. It finds step and roof edges while performing the filtering task.

Local approximations of the brightness function in pairs of opposing neighbourhoods of the analysed pixel are performed, and edge properties are found from differences between the results obtained for these neighbourhoods. Affine approximation is applied, so the detector should work the best for (nearly) piecewise linear brightness functions with additive noise.

Good properties of the detector have been confirmed in experiments with 1D artificial, noisy, and natural functions. The ways of extending the concept to 2D images have been outlined. Work on these extensions is now being carried out. The 2D version of the detector will also indicate the local orientation of the edges.

[1] For better accuracy, larger leaves inclined by a multiple of less than 45° can be applied.

The proposed edge detector can become a valuable tool in analysing selected classes of images. Immediate application is expected in processing the images of ferrite cores, which are characterized by existence of large regions of even brightness with small local defects, and mostly stepwise edges.

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