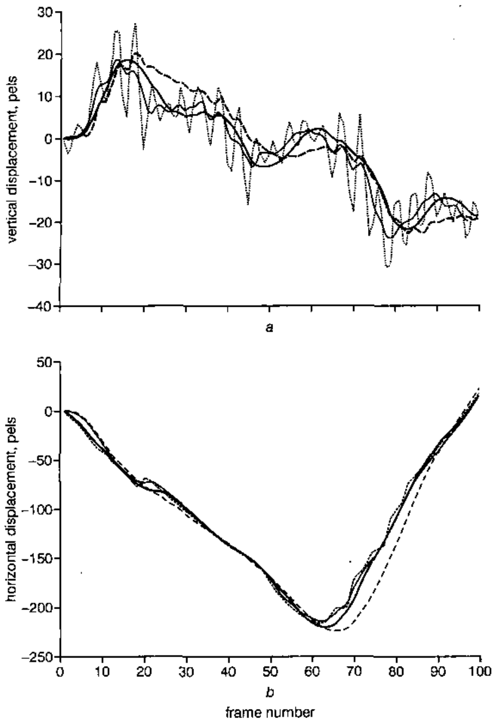

Fig. 2 *Raw, fuzzy adaptive Kalman stabilised, pre-processed (mean filtered) and fuzzy stabilised absolute frame displacements for example sequence*

a Vertical displacement *b* Horizontal displacement
····· raw, – – – fuzzy adaptive Kalman, —— pre-processed, —— fuzzy

A document containing MPEG-1 coded versions of fuzzy stabilised sequences is available at: http://mf.kou.edu.tr/elohab/ipl/research.htm.

Conclusions: An original fuzzy image sequence stabilisation system is presented. The stabilisation system makes use of the feature that fuzzy logic gives superior results for systems which are difficult to control even though the analytical system model is known. It is possible to achieve excellent stabilisation results for sequences using appropriate membership functions, hence future effort is required to adaptively adjust membership functions to achieve optimal performance independent of fluctuation or camera movement characteristics.

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Multiple template detection using impulse restoration and discriminative filters

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Recently, Ben-Arie and Rao have proposed a linear filter that, given a template, maximises the energy concentration in a single sample of its output. A two-dimensional generalisation of this method has also been proposed, formulating template matching as a multivariable optimisation problem. In other work, template detection has been locked at as an impulse restoration problem, and closed-form solutions for it have been proposed. An extension that allows multiple template discrimination is proposed. Simulation results suggest that the proposed method is an effective tool for decision problems and can achieve performances only attainable with sophisticated nonlinear methods.

Introduction: Ben-Arie *et al.* have been working on a type of template detectors referred to as EXM (**EX**pansion **M**atching) [1]. These detectors are based on the optimum decomposition of a signal on a frame constructed from a given template. The success of this method relies on the fact that such expansion is equivalent to filtering the input signal with a linear filter that maximises the energy concentration in one sample of its output. The formulation used there assumes a one-dimensional template.

In [2], a two-dimensional generalisation of the methods in [1] was proposed, based on an impulse restoration approach [3]. In this Letter, we propose an extension that allows multiple template discrimination.

Discriminative filters and impulse restoration: Discriminative filters maximise the energy of an output sample whenever a matching template is found. The two-dimensional discriminative signal to noise ratio ($DSNR_2$), defined in [4], is a measure that accounts not only for the maximum energy of a sample, but also considers its energy in relation to the other samples. Thus, for two-dimensional discriminative filters, we need to maximise:

$$DSNR_2 = \frac{c_{i,j}^2}{(\sum_m \sum_n c_{m,n}^2) - c_{i,j}^2} \qquad (1)$$

The $c_{m,n}$ coefficients are obtained after a two-dimensional convolution between an input image window $\mathbf{U} = \{u_{m,n}\}$ and a linear filter Θ having impulse response $\theta_{m,n}$. Θ is computed for each different template to be matched. The coefficient $c_{i,j}$ is the one where we wish to concentrate the output signal energy.

In the impulse restoration problem [2, 3], one can give an alternative interpretation of discriminative filtering for template detection as follows: the input image $g(m, n)$ can be expressed as

$$g(m, n) = f(m - m_0, n - n_0) + b(m, n) \qquad (2)$$

where $f(m - m_0, n - n_0)$ is the template centred at position (m_0, n_0) and $b(m, n)$ is the rest of the image. Equation (2) can be regarded as the result of an impulse at position (m_0, n_0) being distorted by a linear operator $f(m, n)$ and corrupted with additive noise $b(m, n)$. The ideal discriminative filter would obtain at its output a large value at position (m_0, n_0) and zero otherwise. This is nothing but an impulse; therefore, the ideal discriminative filter is the one that restores the impulse distorted by the template and corrupted with the rest of the image. In earlier work [2], discriminative filtering has been formulated as an impulse restoration problem and, using this formulation, closed form solutions have been found for it. It is important to note that, in previous approaches [4], solutions could only be obtained by numerical optimisation.

It is possible [2, 3] to rewrite (2) in a matrix notation:

$$\boldsymbol{g} = \mathbf{F}\delta + \boldsymbol{b} \qquad (3)$$

where $\boldsymbol{g}$ is the image vector constructed by concatening its transposed rows, $\mathbf{F}$ is a circulant matrix generated by the template, $\boldsymbol{b}$ is the noise vector corresponding to the rest of the image and $\mathbf{C}_b$ is the autocovariance matrix of the noise. As we can see in [2], the optimum linear operator $\mathbf{A}$ is obtained using the following result:

$$\hat{\boldsymbol{\delta}} = \mathbf{A}\boldsymbol{g} = \mathbf{F}^t(\mathbf{F}\mathbf{F}^t + \mathbf{C}_b)^{-1}\boldsymbol{g} \qquad (4)$$

where $\hat{\boldsymbol{\delta}}$ is the estimation of the impulse vector. The circular convolutor filter Θ can be obtained from $\mathbf{A}$ [2].

From this point, we present a novel extension of impulse restoration for multiple template discrimination.

Discriminative filter of type 'OR': In what follows, we propose a discriminative filter that can discriminate more than one template. For example, we show how to design a filter that can discriminate the letters 'A', 'E' and 'O' from other letters. We call such a filter a discriminative filter of the type 'OR'. As in [2], the best estimate $\hat{\delta}$ of δ must satisfy the orthogonality principle [3], that is:

$$E\{(\delta - \hat{\delta})\mathbf{g}^t\} = E\{(\delta - \mathbf{A}\mathbf{g})\mathbf{g}^t\} = 0 \quad (5)$$

Using (3), supposing that the template i corresponds to matrix $\mathbf{F}_i$ and has prior probability p_i, and that δ and $\boldsymbol{b}$ are uncorrelated, (5) becomes:

$$\begin{aligned} E\{(\delta - \hat{\delta})\mathbf{g}^t\} &= E\{(\delta - \mathbf{A}\mathbf{g})\mathbf{g}^t\} \\ &= \sum_i p_i E\{(\delta - \mathbf{A}\mathbf{F}_i\delta - \mathbf{A}\boldsymbol{b})(\mathbf{F}_i\delta + \boldsymbol{b})^t\} = 0 \end{aligned} \quad (6)$$

Consequently,

$$\mathbf{A} = \left\{\sum_i p_i \mathbf{F}_i^t\right\}\left\{\mathbf{C}_b + \sum_i p_i \mathbf{F}_i \mathbf{F}_i^t\right\}^{-1} \quad (7)$$

To exemplify the use of (7), we consider the case where we want to discriminate the letters 'A', 'E' or 'O' from other letters. Assuming that all probabilities p_i are equal, Table 1 shows the $DSNR_2$ values of the filter 'OR' when the filter Θ is applied to the three desired templates 'A', 'E' or 'O' as well as two other letters. Note that the discrimination has been successful.

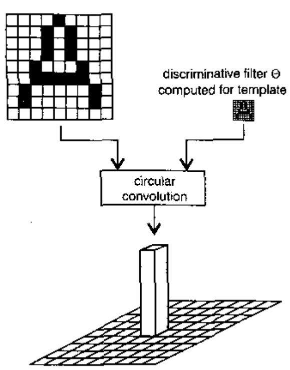

Fig. 1 *Centred impulse*

Discriminative filter of type 'WHICH': As in the previous discussion, the discriminative filter of the type 'OR' can only decide if the image contains a template from the chosen set. However, it cannot determine which of the templates of the set is contained in the input image. In this Section, we propose a change in the computation of the OR filter, in such a way that it can discriminate which of the templates belonging to the set is input to it. We refer to this proposed filter as discriminative filter of the type 'WHICH'.

Table 1: $DSNR_2$ obtained using 'OR' filter of (7)

	Template	$DSNR_2$
'A' (Arial 8pt.)	yes	0.3221
'E' (Arial 8pt.)	yes	0.4153
'O' (Arial 8pt.)	yes	0.7451
'I' (Arial 8pt.)	no	0.0001
'U' (Arial 8pt.)	no	0.0097

Consider the block diagram of Fig. 1. There, we note the fundamental principle of discriminative filtering: the filter Θ, when circularly convolved with the template 'A', offers an output signal with large energy at the centre sample.

Consider now the diagram of Fig. 2. It shows a discriminative filter in which the high-energy output sample is shifted from the centre. Note that the discriminative filter was computed for the template 'A' shifted right and down.

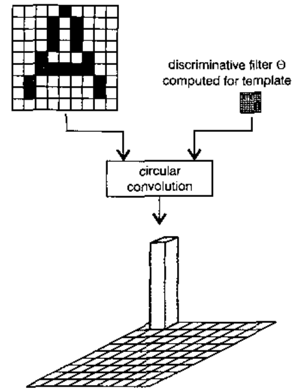

Fig. 2 *Shifted impulse*

Table 2: Stronger sample coordinates and $DSNR_2$ for WHICH filter

	Peak coordinates	$DSNR_2$
'A'	2, 7	0.5888
'E'	8, 6	0.5447
'O'	1, 2	0.8972

Fig. 3 *Filter results*

a Detected 'A', 'E' or 'O' using OR filter *b* Detected 'A' using WHICH filter
c Detected 'E' using WHICH filter *d* Detected 'O' using WHICH filter

As it is possible to shift the large energy sample from the output signal, there is an important alternative to compute the discriminative filter of the type OR: we can chose different shifts for each of the templates. Thus, depending on the highest energy output sample location, it becomes possible to decide which of the templates of the set was input.

As in the previous Section, we take the set {'A', 'E', 'O'} (Arial, 8 pt.), where the shift values are shown in Table 2. Note that, for the three templates, we obtained good values for $DSNR_2$ (greater than 0.5).

Simulation results: We evaluate the proposed discriminative filters by using them to detect 'A', 'E' and 'O' vowels in the Lena image with a text superimposed on it. Fig. 3*a* shows a performance with 100% of correct detections. To obtain the template locations, we took the 9×9 block around each pixel of Lena image and made a circular convolution of it with the 9×9 Θ. After this, we marked all pixel locations where the $DSNR_2$ was larger than 0.240. Fig. 3*b–d* show simulations with the WHICH filter. Note that all letters belonging to the set were detected (the threshold was set to 0.380). All the DSNR obtained for 'A'/'E'/'O' were larger than 0.4050/0.3864/0.4701. In all simulations, no false-alarms occurred.

Conclusions: In this Letter, we presented a novel method, extending the impulse restoration problem for the multiple template detection case. We also proposed a closed-form solution for two types of discriminative filters: the OR filter and the WHICH filter. While the OR filter can only decide if the input image belongs to a set of templates, the WHICH filter can tell which of the templates is the input image. The results obtained indicate that the proposed multiple discrimination method is effective and can be a viable alternative to nonlinear classifiers.

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Variation of ISEF edge detector

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A new algorithm for the recursive infinite symmetric exponential filter (ISEF) edge detector is presented. The proposed algorithm is a cascade of ISEF and a 2 × 2 gradient mask, which will outperform the ISEF (Shen-Castan) edge detector in noise robustness. Experimental evaluations indicate a remarkable improvement in locating edges in very noisy images.

Introduction: An edge detection operator can be considered as a cascade of a lowpass smoothing filter and a derivative operation to localise edges. Shen and Castan [1] presented two algorithms to utilise the ISEF to detect edges. The first algorithm, is based on the recursive ISEF first derivative and it combines the smoothing filter with a [−1 0 1] difference mask. But, as explained in [2], this is not an effective mask for directly approximating the derivative. The second algorithm approximates the Laplacian by subtracting the intensity image from the smoothed image and locates the edges by finding the zero crossings. An adaptive gradient technique is applied for non-maxima suppression. This second algorithm is more commonly used as it gives better results, but it does not provide information about edge orientation. The second algorithm when compared with the Canny algorithm in the evaluation published in [3] ranked first by a slight margin. However, we found a threshold-tuning flaw in that evaluation, which made the Canny algorithm not to produce the best results.

In this Letter, a new variation of the ISEF algorithm is presented that yields significantly better results. Experimental evaluations show that the proposed algorithm performs better than the Canny algorithm when dealing with horizontal and vertical edges even under high noise conditions.

New algorithm: The first derivative of the 1D ISEF in discrete form is given by:

$$\frac{d}{dz}F(z) = b \cdot \left(\frac{1-b}{1+b}\right) \cdot (\ln b) \cdot \left[\frac{z^{-1} - z}{(1 - bz^{-1})(1 - bz)}\right] \quad (1)$$

where b is a positive filter parameter ($0 < b < 1$), and ($z^{-1} - z$) in the numerator corresponds to the basic derivative mask [−1 0 1], the remainder of the expressions is a lowpass filter. The lowpass filter in (1) can be realised by the following difference equations:

$$\text{Forward: } S(n) = Input(n) + b(S(n-1) - Input(n)) \qquad n = 1, \ldots, N \quad (2)$$

$$\text{Backward: } Output(n) = S(n) + b(Output(n+1) - S(n)) \qquad n = N, \ldots, 1 \quad (3)$$

Smoothing parameter: $b = e^{-\alpha}$ ($\alpha \geq 0.2$), $\alpha = 0.2 \rightarrow$ high smoothing.

The *Input* is the original intensity image and *Output* is the smoothed image, S is a temporary parameter, N is the (row or column) size based on the smoothing direction applied. To use this filter the intensity image is embedded in a larger one by applying border reflection. The smoothing operator is then implemented as a cascade of horizontal and vertical applications of (2) and (3).

Instead of using the ($z^{-1} - z$) operator in (1), the gradient components are computed using the 2 × 2 mask [−1 1; −1 1] and its transpose. Non-maxima suppression and hysteresis thresholding are applied to extract the edges.

This proposed filter has the same smoothing capability as that in [1], but the filter structure and realisation as well as the gradient computation technique are significantly different. In addition, the proposed algorithm allows computing edge orientation, which is important in further computer vision stages, i.e. edge matching.

Table 1: Objective evaluation results

	Algorithm	Metric*	$\sigma = 0$	$\sigma = 3$	$\sigma = 9$	$\sigma = 18$
Vertical edge	SUSAN	Pratt	0.78	0.79	Failed	Failed
		Kitchen	1.00	0.76	Failed	Failed
	ISEF	Pratt	0.97	0.93	0.79	0.70
		Kitchen	1.00	0.92	0.58	0.51
	Canny	Pratt	0.97	0.97	0.97	0.93
		Kitchen	1.00	0.94	0.94	0.89
	Proposed	Pratt	0.97	0.97	0.96	0.96
		Kitchen	1.00	1.00	1.00	0.97
Diagonal edge	SUSAN	Pratt	0.95	0.80	Failed	Failed
		Kitchen	1.00	0.90	Failed	Failed
	ISEF	Pratt	0.88	0.90	0.73	0.52
		Kitchen	1.00	0.94	0.52	0.48
	Canny	Pratt	0.97	0.96	0.96	0.95
		Kitchen	1.00	0.97	0.90	0.81
	Proposed	Pratt	0.96	0.97	0.88	0.71
		Kitchen	1.00	0.97	0.64	0.71

*Maximum score = 1

Evaluation of four edge detectors: Three edge detectors are compared with the proposed algorithm. These are, the Canny algorithm, the Shen-Castan second algorithm, and the Smallest Univalue Segment Assimilating Nucleus (SUSAN) edge detector [4]. The evaluation methodology is similar to the one published in [3] and is based on objective metrics as well as a subjective assessment of the detected edges. The Pratt Figure of Merit Rating Factor is used to look for missing edge points, false edge points and smeared edges. The Kitchen and Rosenfeld evaluation metric, is used to evaluate local edge coherence. We have selected two step edges (vertical/diagonal) to test the ability of the detectors to extract edges in different directions, the step edges have been subjected to Gaussian zero-mean noise with σ at 3, 9 and 18. From the results outlined in Table 1, the SUSAN algorithm has failed to extract the edges as noise becomes greater, this being due to the poor smoothing capability of the filter used in the algorithm. For vertical and horizontal edges, the proposed algorithm has the advantage over the other algorithms as the noise level increases. However, it is outperformed in locating diagonal edges by the Canny algorithm with increasing noise level. This is