# On the Evolution of Interest Operators using Genetic Programming

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## Abstract

Interest operators play an important role in computer vision. Depending on the type of the environment some features may prove to be more advantageous than others. Thus detection of interesting features has to be made adaptive such that the best features according to some measure are extracted. We are trying to evolve such feature detectors using genetic programming. In this paper we describe our results where the desired operator, which is a Moravec interest operator, is directly specified. We show that the problem is a rather difficult one. Only an approximation to the Moravec operator could be evolved using several sets of elementary functions.

## 1 Motivation

Interest operators play an important role in computer vision [8]. They highlight points which can be found easily using simple correlation methods. They can be used to calculate accurate distance information and for map building [23]. However no interest operator is suitable for all types of environments. A mobile robot which may be operating in different types of environments should be able to adapt its vision system such that the robot can extract relevant information from its surroundings that can be used best according to some measure.

We are currently trying to equip a mobile robot, a RWI B21 with this type of capability. In this paper we are trying to find a simple interest operator, the Moravec interest operator [23, 22], using genetic programming [14, 15]. The Moravec operator detects points where the minimum of the sum of squared differences between adjacent pixels in four directions, horizontal, vertical and both diagonals is a local maximum. The following section gives a short summary of related work in the area of adaptive feature detection.

## 2 Background

Several researchers used neural nets for adaptive feature detection. Barrow [2] found weights of a neural net to converge into edge masks after the model is being trained on natural images using a Hebbian type learning rule. Linsker [18] showed that a layered self-adaptive neural network developed averaging cells, center-surround cells and orientation selective cells in successive layers using random noise as input and a Hebbian-type learning rule. Joshi and Lee [10, 11] modeled retinal responses using a neural net and showed that the weights learned with the backpropagation learning algorithm approximate the Laplacian of the Gaussian function. Thus backpropagation learns Marr's operator [11]. Lampinen and Oja [17] developed a neural network-based feature extraction and classification system for distortion tolerant pattern recognition. Kohonen [13] developed adaptive feature detectors using an adaptive-subspace self organizing map architecture.

Other researchers used evolutionary algorithms to extract image features. Lohmann [19, 20] evolved an image filter which determined the Euler number of an image using an evolution strategy [25]. Rizki et al. [26] evolved feature detectors which operate on a stack of images to which morphological operations with structuring elements at different resolutions were applied. Roth and Levine [27] extracted geometric primitives using genetic algorithms [7, 6]. Katz and Thrift [12] generated image filters for target recognition using a genetic algorithm. Bhattacharjya and Roysam [3] used evolutionary optimization for model based object recognition at low signal to noise ratios.

Tackett [29, 28] has applied genetic programming to the task of feature classification. He experimented with moment- and intensity features which are extracted from an already segmented region as well as primitive features such as the mean intensity or standard deviation. Tackett used these features in the terminal set of the algorithm, they are not subjected to an adaptive process. Koza [16] evolved detectors for letter recognition which were able to discriminate the letters "I" and "L". The detectors moved themselves over the binary pattern and could analyze the pixels in a local $3 \times 3$ neighborhood. Andre [1] used genetic programming to evolve 2-dimensional feature detectors using $3 \times 3$ hit-miss-matrixes. The task was to discriminate between one designated digit and the rest of the digits. The individuals moved themselves over the image and were able to compare their surroundings with the hit-miss-matrixes. Johnson et al. [9] used genetic programming to evolve Ullman's Visual Routines [30] for the task of determining the location of hands in the bitmap silhouette of a person. Although Johnson et al. are working on real camera data, they are using preprocessed data for the evolution, namely the bitmap silhouette which are binarized images obtained by using a blue screen to segment the person from the background.

We previously used structure evolution, developed by Lohmann [20, 21] a variant of an evolution strategy [25] to evolve hierarchical feature detectors which we applied to the task of character recognition [4]. Using one simple structure changing operator we showed that an increasingly complex detector evolved from simple filter operations. In [5] we evolved edge detectors using genetic programming by approximating the Canny edge detector. In this paper we are focusing on the task of evolving an interest operator. In contrast to the work of Johnson et al. [9] we are working with raw image data that is not preprocessed except for scaling of the pixel intensities.

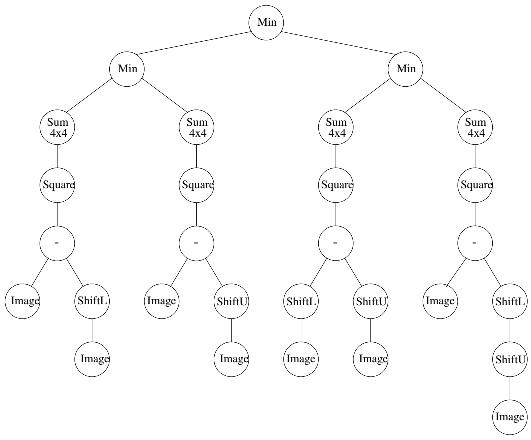


Figure 1: Structure of Moravec operator.

# 3 Evolution of interest operators using genetic programming

To evolve interest operators which are being optimized according to some measure, we are using genetic programming. Thus we need to specify the set of terminals, the set of elementary functions, the fitness measure, the parameters for the run and a criterion to terminate the run [14].

## 3.1 Set of terminals

We selected a gray scale representation of the input image as our sole terminal. The image intensities are scaled to the range [0,1]. Thus the terminal set $T$ becomes $T = \{\text{Image}\}$. Other terminal sets can also be envisaged. For instance one could use the three color bands red, green and blue or hue, saturation and intensity or some combination of them and let evolution select the terminals which are suited best for the task at hand.

## 3.2 Set of primitive functions

The set of primitive functions has to be powerful enough such that the problem at hand may actually be solved. The Moravec interest operator is usually written as

$$
\begin{aligned}
I_R(x,y) = \min\{ & \\
& \sum_{x-2 \le x' < x+2} \sum_{y-2 \le y' < y+2} \left(I(x',y') - I(x'+1,y')\right)^2, \\
& \sum_{x-2 \le x' < x+2} \sum_{y-2 \le y' < y+2} \left(I(x',y') - I(x',y'+1)\right)^2, \\
& \sum_{x-2 \le x' < x+2} \sum_{y-2 \le y' < y+2} \left(I(x'+1,y') - I(x',y'+1)\right)^2, \\
& \sum_{x-2 \le x' < x+2} \sum_{y-2 \le y' < y+2} \left(I(x',y') - I(x'+1,y'+1)\right)^2\}
\end{aligned}
$$

This expression operating on pixel values can be rewritten into an expression consisting entirely of elementary functions operating on whole images. The structure of the Moravec operator using the such elementary functions is shown in figure 1. The resulting image is filtered by suppressing non-local maxima and applying a thresholding operation to extract interesting points from the images.

In the following text the images used as operands are denoted by $I$ or $I_i$ where $i \in \{1, \ldots, 4\}$ and the resulting image is denoted by $I_R$. The following unary functions were used:

Negation (Neg): $I_R(x,y) = -I(x,y)$. Absolute value (Abs): $I_R(x,y) = |I(x,y)|$. Square values (Square): $I_R(x,y) = I(x,y) \cdot I(x,y)$. Shift left (ShiftL): $I_R(x,y) = I(x+1,y)$. Shift right (ShiftR): $I_R(x,y) = I(x-1,y)$. Shift up (ShiftU): $I_R(x,y) = I(x,y+1)$. Shift down (ShiftD): $I_R(x,y) = I(x,y-1)$. Average in $4 \times 4$ area (Avg4x4): $I_R(x,y) = \frac{1}{16}\sum_{-2 \le i,j < 2} I(x+i,y+j)$. Sum in $4 \times 4$ area (Sum4x4): $I_R(x,y) = \sum_{-2 \le i,j < 2} I(x+i,y+j)$.

The following binary functions were used: Subtraction (-): $I_R(x,y) = I_1(x,y) - I_2(x,y)$. Division (/): $I_R(x,y) = I_1(x,y)/I_2(x,y)$. Multiplication (*): $I_R(x,y) = I_1(x,y) \cdot I_2(x,y)$. Addition (+): $I_R(x,y) = I_1(x,y) + I_2(x,y)$. Minimum (Min): $I_R(x,y) = \min\{I_1(x,y), I_2(x,y)\}$. Maximum (Max): $I_R(x,y) = \max\{I_1(x,y), I_2(x,y)\}$.

In addition we used the following N-ary functions ($N \in \{3,4\}$). Multiplication (PiN): $I_R(x,y) = \Pi_{i=1}^{i=N} I_i(x,y)$. Addition (AddN): $I_R(x,y) = \sum_{i=1}^{i=N} I_i(x,y)$. Minimum (MinN): $I_R(x,y) = \min\{I_i(x,y) | i \in \{1,\ldots,N\}\}$. Maximum (MaxN): $I_R(x,y) = \max\{I_i(x,y) | i \in \{1,\ldots,N\}\}$.

| | |
|---|---|
| 1 | BASE |
| 2 | BASE ∪ { Avg4x4 } |
| 3 | BASE ∪ { Sum4x4 } |
| 4 | BASE ∪ { Sum4x4, Pi3, Add3, Max3, Min3 } |
| 5 | BASE ∪ { Sum4x4, Pi3, Add3, Max3, Min3, Pi4, Add4, Max4, Min4 } |

Table 1: Different sets of elementary functions used for the experiments.

## 3.3 Fitness measure

As raw fitness measure to be minimized we selected the squared pixel differences between the actual and the desired output of the operator. For our problem raw fitness equals standardized fitness.

$$
\begin{aligned}
\text{fitness}_{\text{raw}}(\text{Ind}) = \sum_{i=1}^{5} (U(\text{Ind}(\text{I}_i)) + & \\
& \frac{1}{n} \sum_{p \in \text{I}_i} ((\text{Ind}(\text{I}_i))(p) - (\text{Moravec}(\text{I}_i))(p))^2)
\end{aligned}
$$

where the five images for the different fitness cases are given as $\{\text{I}_1, \ldots, \text{I}_5\}$, $p$ is a point from the image and $n$ is the number of points in the image. The evolved operator is denoted by Ind and the desired operator is denoted by Moravec. The term $U(\text{Ind}(I_i))$ evaluates to a large value for a uniform image and to zero otherwise.

# 4 Experiments

We performed five experiments with a population size of 4000 individuals to evolve feature detectors which approximate the response of the Moravec operator. Crossover probability has been set to 85%, reproduction rate has been set to 10% and the mutation rate has been set to 5%. We used ramped half and half initialization and fitness proportionate selection with over-selection. Five fitness cases are evaluated. The five pictures used during the evolution are shown in figure 4. Each run was aborted after 50 generations. For each experiment we performed three different runs. For the experiments we used different sets of elementary functions. The following base set of elementary functions was used for all experiments:

$$\text{BASE} = \{\text{Neg, Abs, Square, ShiftL, ShiftR, ShiftU, ShiftD, -, /, *, +, Max, Min}\}$$

The different sets of elementary functions used for the experiments are shown in table 1.

The base set of elementary functions is sufficient to evolve a Moravec interest operator. There seems to be one elementary function missing, namely Sum4x4. However this elementary function can be constructed using the shift operations and the add operation. The absence of the Sum4x4 elementary function complicates the search for a correct interest operator considerably, because the Sum4x4 elementary function is used 4 times in the correct individual. In each of these places a subroutine performing the desired summation would have to be evolved. This would be a task where automatically defined functions [15] might simplify the problem. We wanted to see what solutions are found if no automatically defined functions are used.

Next we augmented the base set with the operator Avg4x4. Now genetic programming has the possibility of evolving the constant 16 to produce the required elementary function Sum4x4 (e.g. $\text{Sum4x4} = 16 \cdot \text{Avg4x4}$ where $16 = \text{Square}(\text{Square}(\frac{I}{I} + \frac{I}{I}))$. Then we added the required function to the base set. Finally we added the min, max, +, * operators with arity 3 and arities 3 and 4 to the base set.

The best individual of all runs was found in generation 50 using set 5: (Min3 (Sum4x4 (Square (- (Min Image Image) (ShiftU Image)))) (Sum4x4 (Square (- (Neg (- (Min (Abs (Min Image Image)) Image) (ShiftL Image))) (/ (ShiftD (ShiftR (- (Max3 Image Image Image) Image))) (Square (Max3 Image Image Image)))))) (Sum4x4 (Square (- (Neg (- (Min (Abs (Min Image Image)) Image) (ShiftL Image))) (/ (ShiftD (ShiftR (- (Max4 Image Image Image Image) (ShiftR Image)))) (Sum4x4 (ShiftL Image))))))).

Set 3 had the highest average adjusted fitness at generation 50. The structure of the best individuals found with the sets 5 and 3 are shown in figure 2. To make sure that random search by itself did not already produce an interest operator we examined generation 0 of the runs which produced these individuals. The structure found by random search in generation 0 both only emphasize vertical edges. The best individual found with set 5 approximates the Moravec operator quite closely. However, it is not a 100% correct individual. The fitness is especially good for 4 pictures where the sum of the squared pixel differences is less than 0.0005. The result that an interest operator with a seemingly simple structure is rather difficult to evolve is quite surprising. Figure 3 shows the average adjusted fitness of best-of-generation individual for all of the base sets. The features detected by the best evolved interest operator can be seen in figure 4. The first two rows in figure 4 show the result of the Moravec operator. The next two rows show the response of the Moravec operator before a suppression of non-local maxima has been applied. Next, the best individual of generation 0 (found by random search) in the run that produced the closest approximation to the Moravec interest operator is shown. The following two rows show the best approximation to the Moravec interest operator found during the experiments. The final two rows show the features extracted by the best evolved individual superimposed on the original images after the non-local maxima suppression and thresholding operator has been applied.

Note that although the response of the evolved operator approximates the response of the Moravec operator very closely,

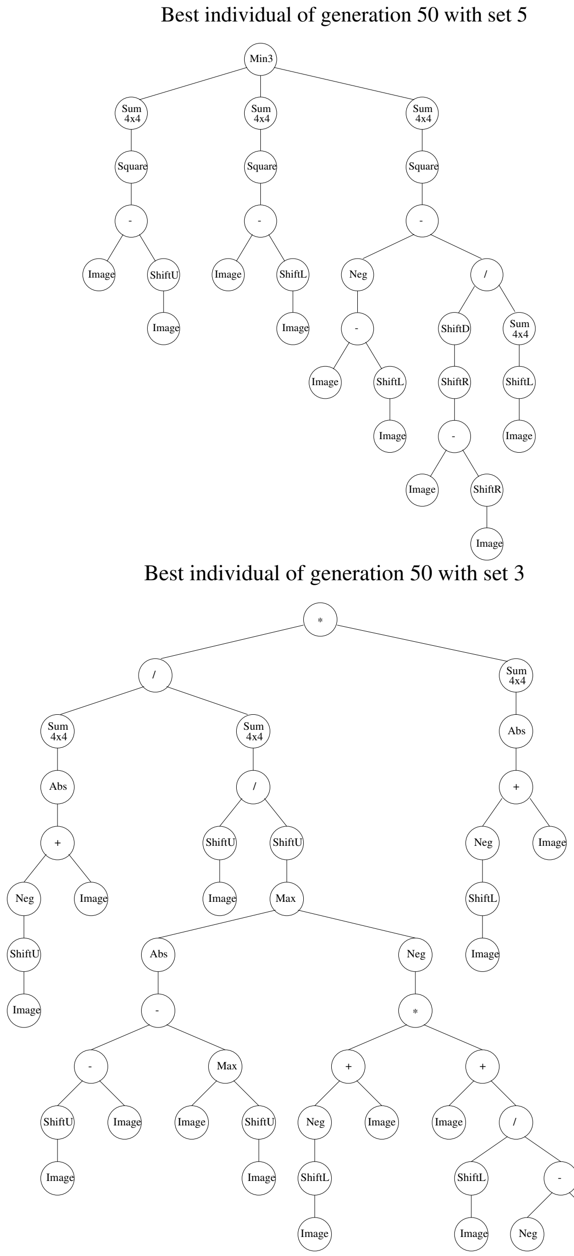


Figure 2: Two best individuals which approximate the Moravec interest operator (the one on top was found using set 5, the one below was found using set 3). Both individuals have been manually simplified.

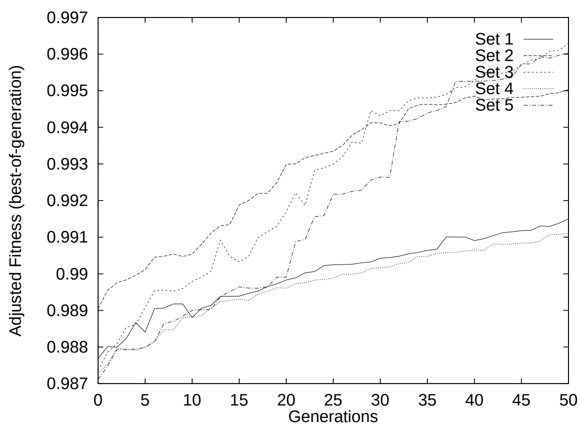


Figure 3: Fitness statistics for all experiments. Each curve has been computed as the average of three runs. Following the standard definition, adjusted fitness is to be maximized.

the actually detected features may still differ. This is due to the fact that a non-local maxima suppression and thresholding operation has been applied that was not included in the fitness function. The task was to approximate the operator response and not to extract the same features. The best evolved interest operator has also been applied to a set of five previously unseen images. The results are shown in Figure 5. The features in the top two rows were extracted with a Moravec interest operator. The next two rows show the response of the Moravec interest operator. The following two rows show the response of the best evolved individual. The final two rows show the features detected by the evolved detector after a non-local maxima suppression and a thresholding operation has been applied.

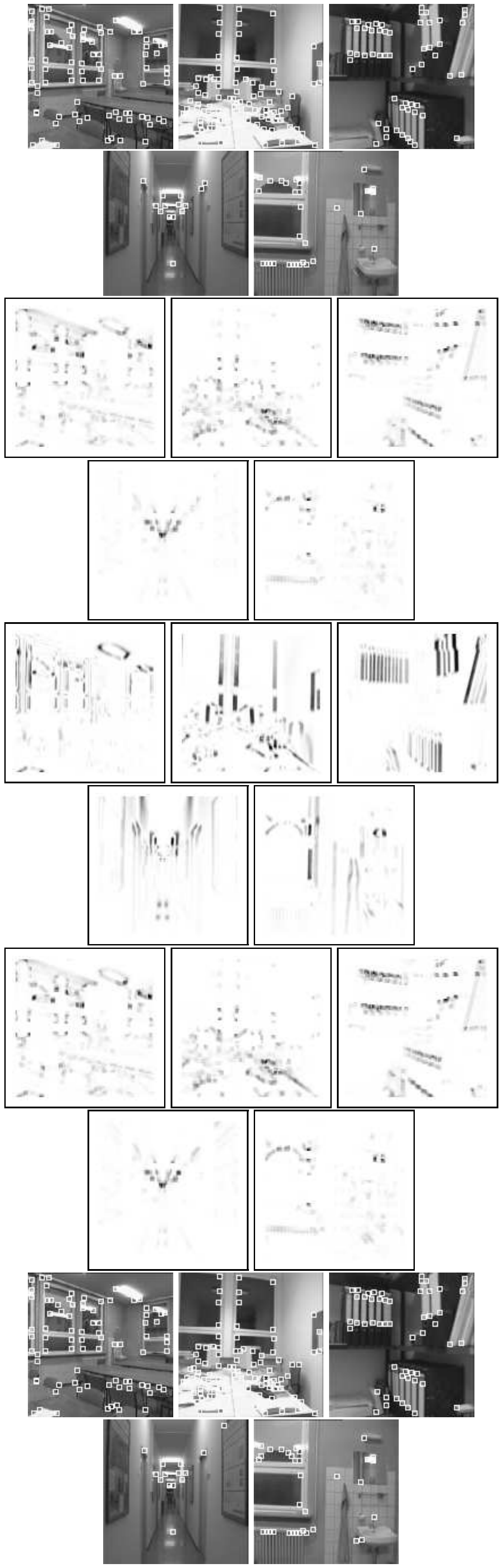

Figure 4: The top two rows show five different images were interesting features have been located which a Moravec operator. The final two rows show the features of the best evolved individual superimposed on the original images after the non-local maxima suppression and thresholding operator has been applied. See text for an explanation of the other images.

# 5 Conclusion and ongoing research

We have shown that genetic programming evolved feature detectors which approximate the Moravec interest operator. However a 100% correct individual has not been found using a population size of 4000 and terminating the evolution after 50 generations. This could be due to the particular structure of the operator at the top of the tree which could be difficult to find.

We are currently experimenting with fitness functions that are not based on any existing operator. Such a fitness measure only describes the desired characteristics of the interest operator. In addition we are experimenting with high level operators such as edge detection, Gaussian smoothing and Gabor filters which augment the set of elementary functions.

# 6 Acknowledgements

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For our experiments we used the lil-gp Programming System, version 1.01 [31]. For image processing we used the Vista software environment [24].

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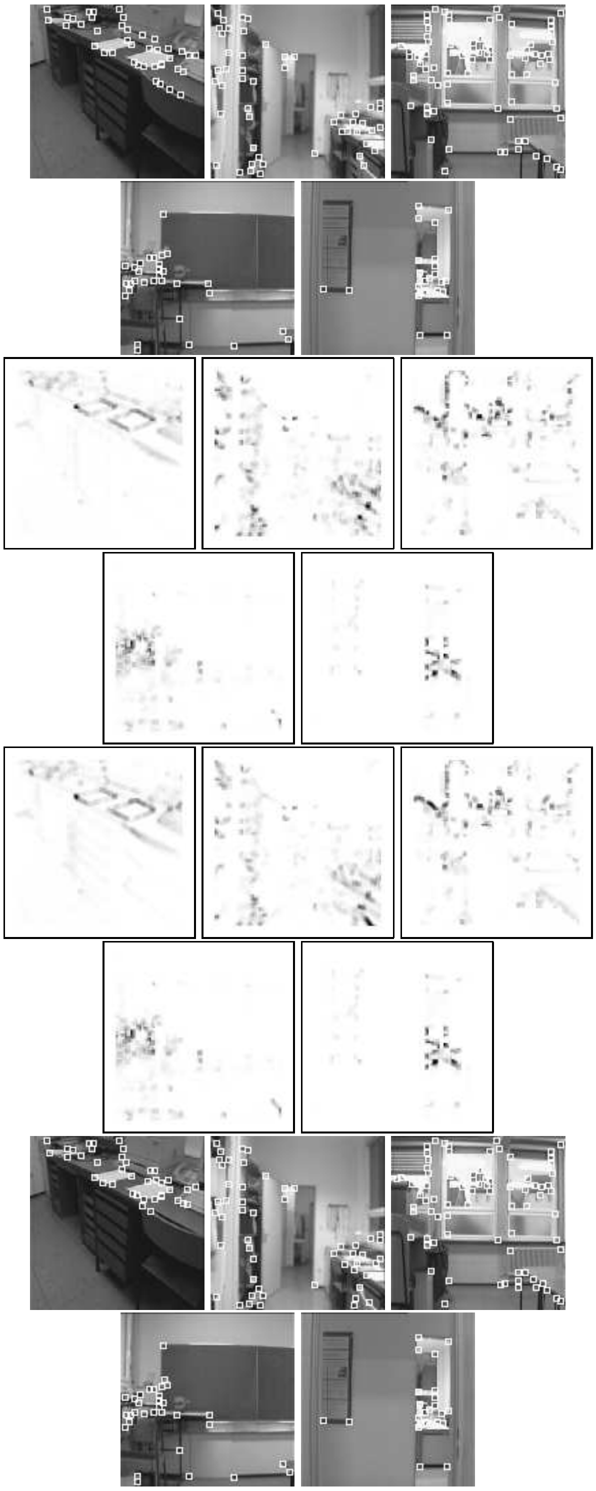

Figure 5: Five images were used to test the evolved interest operators. See text for further explanation.