A SIGNAL-SYMBOL LOOP MECHANISM FOR ENHANCED EDGE EXTRACTION

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Abstract: The transition to symbolic information from images involves in general the loss or misclassification of information. One way to deal with this missing or wrong information is to get feedback from concrete hypotheses derived at a symbolic level to the sub-symbolic (signal) stage to amplify weak information or correct misclassifications. This paper proposes such a feedback mechanism between the symbolic level and the signal level, which we call signal symbol loop. We apply this framework for the detection of low contrast edges making use of predictions based on Rigid Body Motion. Once the Rigid Body Motion is known, the location and the properties of edges at a later frame can be predicted. We use these predictions as feedback to the signal level at a later frame to improve the detection of low contrast edges. We demonstrate our mechanism on a real example, and evaluate the results using an artificial scene, where the ground truth data is available.

1 INTRODUCTION

Processing in most artificial vision systems as well as in the human visual system starts with the extraction of information based on linear and non-linear filtering operations (figure 1) by which, e.g., local orientation, magnitude, and phase become computed. We call this level of processing ‘signal-level’ since the original signal is usually reconstructible from it; i.e., the signal-level information is pixel-wise, continuous and complete.

In a next step, we extract discrete descriptors for line structures using the method of (Krüger et al., 2004). We call this level ‘symbol-level’ since at this stage the semantic information represented in single pixel values is made explicit. Symbolic information is sparse, condensed and semantically rich, and usually, the original signal is not fully reconstructible from it.

Inclusion of contextual information requires the exchange of information over large spatial or temporal distances (in case of, e.g., large object motions or saccades) and even the use of world knowledge stored in long term memory (as for example in the Dalmatian dog illusion (Gregory, 1970)1). Such exchange of information can only be formulated sub-optimally on the signal-level in a pixel-wise representation since the number of pairwise relations would simply become too large or the amount of computer memory required would exceed reasonable bounds. The advantage of a symbolic level is that reasoning over spatial and temporal changes as well as interaction with the world knowledge stored in the memory becomes much easier. In this paper, we introduce a framework of, so called, ‘signal-symbol loops’ and apply it in the context of edge extraction.

The transition to the symbolic level requires the transformation of information at the pixel-wise and continuous signal level to a discrete and condensed symbolic level. This usually requires the use of thresholds. Binary decisions involving such a thresholding usually results in either a loss of information below the threshold or in the extraction of false positives caused by signal noise (see figure 2). In the case of finding line segments, for example, a thresh-

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1The illusion is also available online at http://www.michaelbach.de/ot/cog_dalmatian/index.html
old is introduced to determine contrast sensitivity. Using a high threshold (i.e., low contrast sensitivity) produces reliable (i.e., true positive) but (most of the time) incomplete set of line segments (figure 2). Using a low threshold (i.e., high contrast sensitivity), on the other hand, can produce a more complete set of line segments, which usually include also noisy information (figure 2). This dilemma between incomplete-but-reliable versus complete-but-noisy is faced by all computer vision algorithms which require some thresholding. By local processing alone relevant information can not be distinguished from information caused by, e.g., signal noise or other sources of ambiguity.

One way to gain the information lost during the transition to the symbolic level is to review the signal based on concrete hypotheses generated by reasoning on the symbolic level being fed back to the signal level to amplify the weak but consistent information. We call this feedback mechanism ‘signal-symbol loop’ (see also (Krüger, 2005)).

To make information at the symbolic level comparable to the signal, it is required to transform the symbolic information back in a form that makes it comparable to the signal level. This transformation can be regarded as taking the inverse of a symbolic description, and therefore it is called the feedback function in the rest of the paper. This feedback function can be considered as the inverse of a symbol since it transforms the symbolic information back to the signal-level.
level information.

This paper proposes a concrete signal-symbol loop mechanism to improve the extraction of low-contrast edges by making use of motion information, namely, the change of a symbolic local edge descriptor under a Rigid Body Motion (RBM). In our paper, the change of position and orientation of this descriptor under an RBM can be formulated explicitly: After estimating the position of a 3D edge descriptor at a later frame, the image projection of the estimated 3D descriptor provides feedback to the filter processing level. The feedback information states that there must be an edge descriptor with certain properties at a certain position. The filter processing level then enhances the information at a position if the feedback is consistent with the original image information. The rough outline of the mechanism that we propose is given in figure 1.

The approach we introduce here is related to 'adaptive thresholding' approaches which are for example used in the area of image segmentation. These can also recover low-contrast edges by adjusting the threshold. This adjustment, however, is based on the local distribution of image intensities (see, e.g., (Gonzalez and Woods, 1992)). Our approach differs from adaptive thresholding since it makes use of symbolic information that facilitates a more global and also a more directed mechanism rather than local intensity distribution. Moreover, as we discuss at the end of the paper, the novelty of the current paper is in the proposal of a symbol-to-signal feedback mechanism that can be applied also in other contexts.

The idea of using of feedback in vision systems is not new (Aloimonos and Shulman, 1989; Angelucci et al., 2002; Galuske et al., 2002; Bullier, 2001). For computational models the interested reader is directed for example to (Bayerl and Neumann, 2007) for modelling at the neuronal level for long-range information exchange between neurons. Our work is different from the above mentioned works in that we introduce a feedback mechanism between different layers of processing, i.e., the signal-level and the symbol-level, and we apply it in a different context.

The paper is organized as follows: In section 2, we introduce the symbolic edge descriptors and the concept of RBM that are utilized in this paper. Section 3 describes our feedback mechanism. In section 4, we present and discuss the results, and the paper is concluded in section 5.

2 SYMBOLIC DESCRIPTORS AND PREDICTIONS

In this section, we give a brief description of the image descriptors that we use to represent local scene information at the symbolic level (section 2.1). These descriptors represent local image information in a condensed way and by that transform the local signal information to a symbolic level. In section 2.2, we briefly comment on Rigid Body Motion which we use as the underlying regularity of predictions on the symbolic level.

2.1 Multi-modal Primitives

The concept of multi-modal primitives has been first introduced in (Krüger et al., 2004). These primitives are local multi-modal scene descriptors, which are motivated by the hyper-columnar structures in V1 (Hubel and Wiesel, 1969).

In its current state, primitives can be edge-like or homogeneous and carry 2D or 3D information. For the current paper, only edge-like primitives are relevant. An edge-like 2D primitive (figure 3(a)) is defined as:

$$\pi = (x, \Theta, \omega, (\xi_l, c_m, \xi_r))$$ (1)

where \(x\) is the image position of the primitive; \(\Theta\) is the 2D orientation; \(\omega\) represents the local phase, the color is coded as three vectors \((\xi_l, c_m, \xi_r)\), corresponding to the left \((c_l)\), the middle \((c_m)\) and the right side \((c_r)\) of the primitive. See (Krüger et al., 2004) for more information about these modalities and their extraction. Figure 4 shows the extracted primitives for an example scene.

A primitive \(\pi\) is a 2D descriptor which can be used to find correspondences in a stereo framework to create 3D primitives (as introduced in (Krüger et al., 2004)) which have the following formulation:

$$\Pi = (X, \Theta, \Omega, (\xi_l, c_m, \xi_r))$$ (2)
Appearance based information is coded by generalising local phase and color of the two corresponding 2D primitives. The reconstruction of a 3D primitive from two corresponding 2D primitives is exemplified in Figure 3(b).

Knowledge of the RBM allows estimation of the 3D entities, in our case the primitives, at a later frame:

$$\hat{\Pi}_{t+\Delta t} = \text{RBM}_{t \rightarrow t+\Delta t}(\Pi_t).$$

(5)

In this paper, the ground truth RBM is known either because the scene is generated using OpenGL, or because the object is rotated with a robot arm whose motion is known. See (Faugeras, 1993) for more information about RBM and RBM estimation methods.

3 FORMALIZATION OF THE SIGNAL-SYMBOL LOOP

The RBM predicts a 3D primitive at a later frame. This prediction is formulated at the symbolic level since it uses the 3D primitives. The projection of this primitive from the symbolic level into the image (using the projection relation defined in equation 3) provides a position and an orientation feedback to the filtering operations (i.e., the signal level). At the filtering-processing level, this feedback at discrete positions is combined with the extracted filter responses.

At the signal level, we use complex Gabor wavelets as a basic filtering operation (Lee, 1996). The Complex Gabor wavelet response $G$ is computed on eight different orientations; i.e., $G(x, y, c_i)$ for $i \in [1, 8]$ (figure 5). The feedback of a prediction with image coordinate $(x_0, y_0)$ and orientation $\theta_0$ (falling into channel $c_0$)\(^2\) is distributed over the Gabor channels

$$G(x, y, c_i)$$

\(^2\)The channel $c_i$ that an orientation $\theta \in [0, \pi)$ corresponds to is computed using $i = \text{round}(N \cdot \theta / \pi)$ where $N = 8$ is the total number of channels.
using the following Gaussian Feedback Function:

$$ F(x, y, c_i) = \frac{1}{C} \exp \left( -\frac{1}{2} \left\{ \frac{(x-x_0)\cos\theta_0 + (y-y_0)\sin\theta_0}{\sigma_x} + \frac{-(x-x_0)\sin\theta_0 + (y-y_0)\cos\theta_0}{\sigma_y} + \frac{(c_j - c_0)^2}{\sigma_c} \right\} \right), \quad (6) $$

where $C$ is a normalization constant computed using:

$$ C = \frac{1}{(2\pi)^{1/2}(\sigma_x^2 + \sigma_y^2 + \sigma_c^2)}, \quad (7) $$

where we empirically set $\sigma_x = 4, \sigma_y = 1, \sigma_\theta = 1$. The Gaussian Feedback Function in equation 6 is an essential part of the signal-symbol loop proposed in this paper since it distributes the incomplete, condensed and discrete symbolic information in a 2D primitive $\hat{\mathbf{p}} = \mathcal{F}(\mathbf{RBM}(\mathbf{p}))$ to the complete, continuous and pixel-wise signal-level information: i.e., $F(\hat{\mathbf{p}}) = F(x, y, c_i)$ for $i = 1, \ldots, 8$.

The original Gabor responses and the feedback $F(x, y, c_i)$ from the symbolic level, i.e., RBM estimation, are combined into a modified Gabor function $\hat{G}(x, y, c_i)$ as follows:

$$ \hat{G}^R(x, y, c_i) = G^R(x, y, c_i) + w \cdot F(x, y, c_i), \quad (8) $$

$$ \hat{G}^I(x, y, c_i) = G^I(x, y, c_i) + w \cdot F(x, y, c_i). \quad (9) $$

where $G^R$ and $G^I$ are the complex and the imaginary parts of the respective orientation channels. We determine the weight $w$ based on the consistency of the predicted orientation (i.e., the orientation of the 2D projection of the predicted 3D primitive) with the extracted Gabor responses as follows:

$$ w = \left[ 1 - \frac{1}{N \cdot \pi / 2} \sum_{(x', y') \in \Omega} \theta_0 - \theta_{c_i}(x', y') \right], \quad (10) $$

where $\theta_0$ is the predicted orientation, the variables $(x', y')$ run over a local neighborhood $\Omega$ whose size is $N$.

From the complex filter responses on eight channels, the magnitude $m$ and the orientation $\theta$ are trivial to compute, and the details are skipped (see, e.g., (Haglund and Fleet, 1994)).

4 RESULTS

In this section, we present and evaluate the results of our mechanism on an artificial (section 4.1) and a real scene (section 4.2).
4.2 Real Scene

The real scene involves a robot arm and an object grasped by the robot arm (figure 9). The robot arm executes a known RBM, and our system uses the RBM to improve the feature extraction.

Figure 10(a) shows the extracted primitives without feedback. We see that some of the edges are not extracted due to low contrast. However, the knowledge of RBM can feedback and improve the extraction of the edges (figure 10(b)). Figures 10(c) and (d) show that the extraction of the magnitude is improved with the feedback.

5 CONCLUSIONS

This paper has proposed a novel feedback mechanism to improve the extraction of low contrast edges. Specific for this mechanism is that information is transformed to a symbolic level on which symbolic reasoning leads to predictions that then become fed back to the signal level. For this, the prediction that has been generated on a symbolic level needs to be inverted to become comparable at the signal level.

In the current paper, symbolic reasoning is restricted to the change of a symbolic descriptor under a rigid body motion. However, we claim that the introduced mechanism is also applicable to other forms of symbolic reasoning, for example by using stored object knowledge to predict edges at weak structures after an object hypothesis has been aligned with the current scene (as for example in the Dalmatian dog illusion (Gregory, 1970)). These issues are being addressed in our ongoing research.

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Figure 9: (a)-(b) Left and right frames at time $t$. (c) 3D primitives at time $t$ (extracted from (a) and (b)). (d) The projection of the predicted 3D primitives in (c) shown over the image taken at frame $t + 1$.

REFERENCES


Figure 10: (a) The primitives extracted at frame $t+1$ without feedback. (b) The primitives extracted at frame at $t+1$ with feedback. The gray area denotes the extracted descriptors which are lost without feedback mechanism. (c) The magnitude image of frame $t+1$ without feedback. (d) The magnitude image of the updated frame at $t+1$ with feedback.