An Elaboration on
Order-Adaptive Regularisation for Variational Optical Flow: Global, Local and in Between

Hauptseminar Recent Advances in Computer Vision

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Abstract—Hier sollte eine kurze Zusammenfassung der Ausarbeitung stehen. Der Umfang sollte 150 bis 250 Worte betragen. Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie consequat, vel illum dolore eu feugiat nulla facilisis at vero eros et accumsan et iusto odio dignissim qui blandit praesent luptatum zzril delenit augue duis dolore te feugait nulla facilisi. Lorem ipsum dolor sit amet, consectetuer adipiscing elit, sed diam nonummy nibh euismod tincidunt ut laoreet dolore magna aliquam erat volutpat. Ut wisi enim ad minim veniam, quis nostrud exerci tation ullamcorper suscipit lobortis nisl ut aliquip ex ea commodo consequat. Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie consequat, vel illum dolore eu feugiat nulla facilisis at vero eros et accumsan et iusto odio dignissim qui blandit praesent luptatum zzril delenit augue duis dolore te feugait nulla facilisi.

1 Introduction

In computer vision, the field of optic flow deals with the estimation of a 2-dimensional flow field based on two consecutive frames of an image sequence.
(mehr dazu warum optic flow geil ist)
Different methods for flow estimation exist, such as ... ... and variational optic flow which is based on the calculus of variations. In the following the concept of variational flow estimation is recapitulated and the approach by Maurer, Stoll and Bruhn [3] with order adaptive regulalarization is presented.

2 Variational Optic Flow

In this section the general framework for flow estimation using variational methods is recapitulated.

Given two subsequent images of an image sequence
$I_0, I_1 \; : \; \Omega \subset \mathbb{R}^2 \to \mathbb{R}$,
we seek the displacement vector field
$\vec{u} = (u \; v)^\top \; : \; \Omega \subset \mathbb{R}^2 \to \mathbb{R}^2$
that maps I_0 onto I_1 such that
$I_0(\vec{x}) = I_1(\vec{x} + \vec{u}(\vec{x}))$.

To estimate the flow function $\vec{u}$ an energy functional is minimized. Typically this functional consists of two terms, a data term $D(\vec{u})$ and a regularization term $R(\vec{u})$.

$$\vec{u}' = \underset{\vec{u}}{\operatorname{argmin}} E(\vec{u})$$
$$E(\vec{u}) = D(\vec{u}) + \alpha R(\vec{u})$$

In this framework, the data term is used to penalize flow functions which violate certain constancy assumptions on image features, such as the brightness constancy assumtion.

$$D_{brght}(\vec{u}) = \int_\Omega (I_0(\vec{x}) - I_1(\vec{x} + \vec{u}(\vec{x}))^2 \, d\vec{x}$$

As the data term is insufficient for solving this problem and would yield multiple ambiguous solutions as illustrated in fig. 1, the regularization term is used to overcome this inconvenience and penalize flow functions that are unlikely. This is done by setting up constraints for the flow, such as the first order smoothness assumption.

$$R_{smooth}(\vec{u}) = \int_\Omega ||\nabla u||_2^2 + ||\nabla v||_2^2 \, d\vec{x}$$

This assumption enforces constant flow due to penalizing non vanishing gradients, which amount to changes in the vector field.

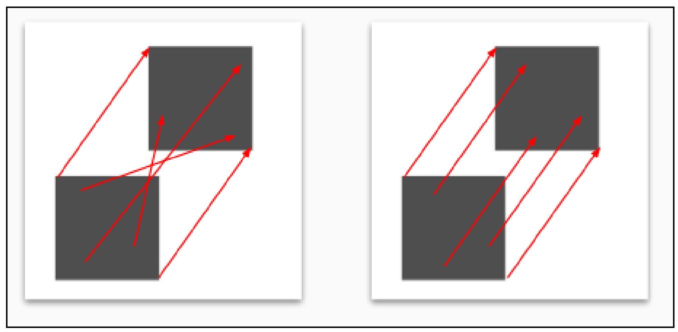

Figure 1: Images show a rectangle that moved from bottom left to top right. The red arrows sketch a flow field explaining where the pixels moved. Even though both fields perfectly fulfill a data term with brightness and gradient constancy assumption, only the right field is reasonable and would minimize a first order smoothness regularization.

In order to minimize the energy functional, an iterative update sheme is developed using the Euler-Lagrange equation [4].

3 Motivation

As explained in section 2 the regularization term can be used to constrain the "type" of the estimated flow function. In practice either first or second order smoothness assumptions are made in which a flow function minimizes the regularization term when its first or second derivative vanishes. Therefore, first order methods are suitable for motion that is constant, i.e. parallel to the image plane. Second order methods can be leveraged for estimating affine flow fields as the class of linear functions implies vanishing second derivative. Figure 2 shows a constant and linear flow field for comparison.

Depending on the situation in the image sequence, a constant flow field may be more reasonable than a linear one. Imagine for example a sequence captured from the view point of a car driver who waits at a crossing while other cars pass the crossing from left to right in front of him. The optic flow in this situation would be constant as all cars move in the same direction parallel to the image plane. Now imagine the car driver moving forwards as the crosisng is now free, the whole scene around him will appear to move towards him. The optic flow is now linear as the surroundings move perpendicular to the image

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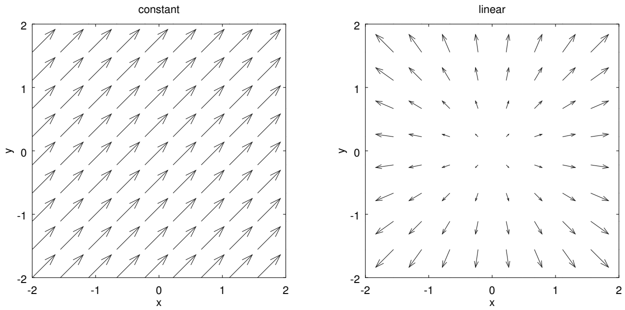

Figure 2: Graphs show vector fields of different behaviour, left is constant with $f(x,y) = (1\ 1)^\top$, right is linear with $f(x,y) = (x\ y)^\top$. Constant flow is typical for motion parallel to the image plane, linear flow for motion orthogonal to the image plane.

plane. However, the flow behaviour is not exclusive, both constant and linear flow can be present in the same sequence, for example when another car heading in the same direction switches lanes. To account for such situations, a variational model has to make more sophisticated assumptions than simple first or second order smoothness.

Fortunately, the presented approach manages to combine first and second order regularisation and even adaptively choose optimal order for a given sequence. Moreover it provides different adaption shemes to enable a global, local, non-local and region based selection of regularisation.

4 Variational Model

In this section the variational model by Maurer, Stoll and Bruhn introduced in their work [3] will be discussed in detail. As said in section 3 the variational model is able to adaptively choose regularization order. Therfore the regularisation term is a combination of a first and a second order part. First the models data term is discussed followed by the first and second order part of the regularization and their underlying concepts.

4.1 Dataterm

The employed data term in the variational model uses a combination of brightness and gradient constancy assumption.

$$D(\vec{u}) = \int_\Omega \psi_{\mathrm{Ch}}(p_{\mathrm{brght}}(\vec{u})) + \gamma \cdot \psi_{\mathrm{Ch}}(p_{\mathrm{grad}}(\vec{u}))\, d\vec{x} \tag{1}$$

$$p_{\mathrm{brght}}(\vec{u}) = (\ I_1(\vec{x}+\vec{u}(\vec{x})) - I_0(\vec{x})\ )^2 \tag{2}$$

$$p_{\mathrm{grad}}(\vec{u}) = ||\ \nabla I_1(\vec{x}+\vec{u}(\vec{x})) - \nabla I_0(\vec{x})\ ||_2^2 \tag{3}$$

In this setup, p_{brght} is the penalizer for the brightness constancy assumption and p_{grad} is the penalizer for the gradient constancy assumption which can be understood as a check for edges being mapped correctly. The parameter γ is used to weight the terms against each other. As can be seen p_{brght} and p_{grad} are quadratic penalizers, and are thus sensitive to outliers. To remove the strong influence of outliers on the minimization, the subquadratic charbonnier penalizer [1] ψ_{Ch} is used to robustify both constancy assumptions.

$$\psi_{\mathrm{Ch}}(s^2) = 2\varepsilon^2 \sqrt{1 + s^2/\varepsilon^2} \tag{4}$$

Note that the charbonnier penalizer is a function of a squared argument so that an arbitrary quadratically penalized assumption can be plugged in. When plotting the function with respect to s instead of s^2 its behaviour becomes clearer, as shown in fig. 3. For values close to zero, the function penalizes quadratically and approaches linear behaviour in the limit $s \to \pm\infty$, resulting in outliers being less fatal.

4.2 First Order Regularizer

The first order term of the regularization is the anisotropic complementary regulariser by Zimmer et al. [5].

$$R_{\mathrm{1st}}(\vec{u}) = \int_\Omega S_1(\vec{u})\, d\vec{x} \tag{5}$$

$$S_1(\vec{u}) = \psi_{\mathrm{PM}}\Big((\vec{r}_1^\top \nabla u)^2 + (\vec{r}_1^\top \nabla v)^2\Big) + \psi_{\mathrm{Ch}}\Big((\vec{r}_2^\top \nabla u)^2 + (\vec{r}_2^\top \nabla v)^2\Big) \tag{6}$$

This term makes use of the eigenvectors of the regularisation tensor [5]. The regularization tensor is a generalization of the structure tensor [2] for arbitrary image features. In short, it summarizes gradient information within a neighborhood of a pixel. The eigenvector $\vec{r}_1$ points in the direction of steepest change (i.e. over an edge) while $\vec{r}_2$ is orthogonal to $\vec{r}_1$ (i.e. points along an edge).

Lets postpone the discussion of the regularization tensor for a second and get some intuition on the way S_1 works. As can be seen from eq. (6), the term uses two penalizer functions, the Charbonnier penalizer which was introduced in section 4.1 in eq. (4) and the Perona Malik penalizer ψ_{PM}.

$$\psi_{\mathrm{PM}}(s^2) = \varepsilon^2 \ln(1 + s^2/\varepsilon^2) \tag{7}$$

As arguments to the penalizer functions, projections of the flow gradients onto the eigenvectors are used. These projections are minimal if the flow gradient vanishes as in standard first order smoothness terms. Special about this term are the different penalizations of projections on the first and second eigenvector respectively. The graphs of the two penalizer functions are shown in fig. 3, where it can be seen that values close to zero are penalized quadratically, values further away are penalized subquadratically in both functions. In the limit however, the Perona-Malik penalizer takes on smaller values than the charbonnier penalizer. This has the effect of flow changes tangent to the first eigenvector to be less costly than tangent to the second eigenvector. From the perspective of image features and the regularization tensor this is like getting a “discount” on flow change over an edge.

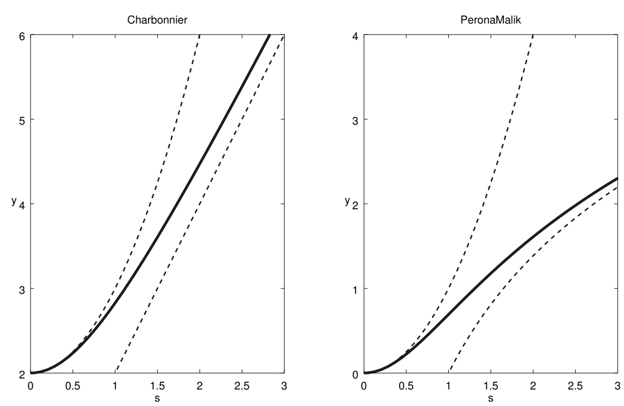

Figure 3: Graphs show penalizer functions and their asymptotic equivalents as dashed lines.
Left is charbonnier eq. (4) with $\varepsilon = 1$ and asymptotic equivalents $\lim_{s\to 0} \psi_{\mathrm{Ch}}(s^2) = s^2 + 2$ and $\lim_{s\to\infty} \psi_{\mathrm{Ch}}(s^2) = 2s$.
Right is Perona Malik eq. (7) with $\varepsilon = 1$ and asymptotic equivalents $\lim_{s\to 0} \psi_{\mathrm{PM}}(s^2) = s^2$ and $\lim_{s\to\infty} \psi_{\mathrm{PM}}(s^2) = 2\ln(s)$.

4.2.1 Regularization Tensor

To continue the discussion of the regularization tensor, lets state its definition first.

$$\mathcal{S}_{\Phi,\omega}(\vec{x}) = \int \omega(\tau) \begin{pmatrix} \Phi_x(\vec{x}-\tau)^2 & \Phi_x(\vec{x}-\tau)\Phi_y(\vec{x}-\tau) \\ \Phi_x(\vec{x}-\tau)\Phi_y(\vec{x}-\tau) & \Phi_y(\vec{x}-\tau)^2 \end{pmatrix} d\tau \tag{8}$$

$$\mathcal{S}_{\Phi,\omega} = Q\Lambda Q^\top = \begin{pmatrix} \vec{r}_1 & \vec{r}_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} \vec{r}_1^\top \\ \vec{r}_2^\top \end{pmatrix} \tag{9}$$

The tensor is a convolution of a weighting function ω with a matrix. The matrix is the outer product of the gradient of the selected image feature Φ which is calculated as $\nabla\Phi(\vec{x})\nabla\Phi(\vec{x})^\top$. For the structure tensor the image feature would be brightness $\Phi = I$, but as this is the generalization, Φ can be something else like the saturation value in HSV color space or luminance of CIE L*a*b*. Typically, the feature is chosen to be consistent with the feature used in the data term, which would be a combination of brightness and gradient norm. Using the eigendecomposition (eq. (9)), the orthonormal eigenvectors $\vec{r}_1$ and $\vec{r}_2$ are obtained which summarize the gradient distribution in the neighborhood defined by the weighting function ω. If the weighting function was a Dirac delta $\omega = \delta$ the eigendecomposition of the tensor would yield the normalized gradient as first eigenvector.

$$\mathcal{S}_{\Phi,\delta} = \nabla\Phi\nabla\Phi^\top = \lambda_1 \cdot \vec{r}_1\vec{r}_1^\top = \begin{pmatrix} \vec{r}_1 & \vec{r}_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \vec{r}_1^\top \\ \vec{r}_2^\top \end{pmatrix}$$

Here the first eigenvalue is the squared length of the gradient $\lambda_1 = |\nabla\Phi|^2$. Of course this discussion only holds for Dirac delta as weighting function, for others like Gaussian, the eigenvectors cannot be factored in this way.

4.3 Second Order Regularizer

The second order regularizer makes use of two auxiliary functions $\vec{a}(\vec{x})$ and $\vec{b}(\vec{x})$ which are connected to the flow $\vec{u}$ using a coupling term S_2. These auxiliary functions are as well unknown and are controlled by an auxiliary smoothness term S_{aux}.

$$R_{\text{2nd}}(\vec{u}) = \int_\Omega \inf_{\vec{a},\vec{b}} \left[\, S_2(\vec{u},\vec{a},\vec{b}) + \beta \cdot S_{\text{aux}}(\vec{a},\vec{b}) \,\right] d\vec{x} \tag{10}$$

$$\begin{aligned} S_2(\vec{u},\vec{a},\vec{b}) &= \psi_{\text{PM}}\Big((\vec{r}_1^\top(\nabla u - \vec{a}))^2 + (\vec{r}_1^\top(\nabla v - \vec{b}))^2 \Big) \qquad (11) \\ &\quad + \psi_{\text{Ch}}\Big((\vec{r}_2^\top(\nabla u - \vec{a}))^2 + (\vec{r}_2^\top(\nabla v - \vec{b}))^2 \Big) \\ S_{\text{aux}}(\vec{a},\vec{b}) &= \psi_{\text{PM}}\Big(\textstyle\sum_{k=1}^2 (\vec{r}_k^\top \mathcal{J}_{\vec{a}}\, \vec{r}_1)^2 + (\vec{r}_k^\top \mathcal{J}_{\vec{b}}\, \vec{r}_1)^2 \Big) \qquad (12) \\ &\quad + \psi_{\text{Ch}}\Big(\textstyle\sum_{k=1}^2 (\vec{r}_k^\top \mathcal{J}_{\vec{a}}\, \vec{r}_2)^2 + (\vec{r}_k^\top \mathcal{J}_{\vec{b}}\, \vec{r}_2)^2 \Big) \end{aligned}$$

This regularization term can be interpreted as the integral over the infimal convolution of S_2 and S_{aux} with respect to the vector fields $\vec{a}$ and $\vec{b}$.

The coupling term S_2 is similar to the first order term S_1 in that it uses the two penalizer functions ψ_{PM} and ψ_{Ch} to penalize non zero projections with respect to the eigenvectors of the structure tensor (eq. (8)). This time however, not the flow gradients themselves are projected, but the differece of the gradients to the auxiliary functions. The coupling term therefore becomes minimal if the gradients are euqal to the auxiliary functions instead of equal to zero as in the first order term. Again, the prejection on the first eigenvector is penalized less due to the behavior of the perona malik penalizer, but is not intuitive in the form written above. If instead we reformulate the projection as $(\vec{r}_1^\top(\nabla u - \vec{a}))^2 = (\vec{r}_1^\top\nabla u - \vec{r}_1^\top\vec{a})^2$ it becomes clear that the flow gradient and the auxiliary function are allowed to differ as long as they are roughly tangent to the first eigenvector.

In the auxiliary term S_{aux} the Jacobians of the auxiliary functions $\mathcal{J}_{\vec{a}}$ and $\mathcal{J}_{\vec{b}}$ are anisotropically penalized similar to the first order penalization of the flow gradients. Obviously, the auxiliary term is minimal if the derivatives of the auxiliary functions vanish, allowing for constant auxiliary functions with changes at edges which are indicated by the regularization tensor. Due to the connection of the auxiliary functions to the flow gradients in the coupling term, the flow is indirectly constrained to be linear. This is because the nullspace of the second order term are functions with derivatives equal to the auxiliary functions which are constrained to be constant.

5 Order Adaption

In section 4, the data and regularization terms were discussed and it was explained that the first order regularizer enforces constant flow whereas the second order regularizer allows for linear flow. As illustrated in fig. 2 constant vector fields are suitable for modelling motion parallel to the image plane, motion orthogonal to the image plane can be modelled using a linear flow field. So what is needed to apply the most suitable regularizer depending on the current sequence, is an adaptive scheme. In the following four different schemes will be discussed, where the global scheme will be used to introduce the underlying concept of the schemes.

5.1 Global Scheme

The global adaptive scheme will be choosing order once for the whole image domain. To do so a general regularization term consisting of both, first and second order, will be extended. The general regularization term is a simple convex combination of the terms with weighting parameter $c \in [0,1]$ and selecton term $\phi_\lambda(c)$ of the following form.

$$\begin{aligned} R(\vec{u},c) = \int_\Omega \inf_{\vec{a},\vec{b}} \big[\, & c \cdot S_1(\vec{u}) + (1-c) \cdot S_2(\vec{u},\vec{a},\vec{b}) \qquad (13) \\ & + \beta \cdot S_{\text{aux}}(\vec{a},\vec{b}) + \phi_\lambda(c) \,\big]\, d\vec{x} \end{aligned}$$

It may be counter intuitive to only include S_1 and S_2 in the convex combination and not S_{aux}, but S_{aux} is independent of $\vec{u}$ and merely used to constrain the auxiliary functions. S_1 and S_2 on the other hand are the energies with respect to the flow and are comparable to each other as they only differ in the projected quantity, which was already discussed in section 4.3. The goal thus, is to embed some information into the the weighting parameter c such that it equals to 1 when first order regularization has less energy than second order regularization and equals to 0 in the contrary case. However, since the class of linear functions which can be modelled using second order regularization includes constant functions, it is only desirable to use second order regularization when it yields a significant benefit over first order. To model this behavour of c a sigmoid function of the benefit Δ of first over second order regularization is used as illustrated in fig. 4.

$$c = \frac{1}{1+e^{-\Delta/\lambda}} \quad \text{with} \quad \Delta = T + \frac{1}{|\Omega|}\int_\Omega S_2 - S_1 \, d\vec{x} \tag{14}$$

Here λ is used to control the slope of the sigmoid function, and T is the threshold by which the second order regularizer has to be better than first order, so that second order will be used.

To get to this behavior of c from the euler lagrange equation's point of view, the corresponding selection term $\phi_\lambda(c)$ has to be found. By examining the regularizers partial derivative $\frac{\partial R}{\partial c} = 0$ we get to the following equation.

$$\begin{aligned} \frac{\partial R(\vec{u},c)}{\partial c} &= \int_\Omega S_1(\vec{u}) - S_2(\vec{u},\vec{a},\vec{b}) + \phi'_\lambda(c)\, d\vec{x} \;=\; 0 \\ -\phi'_\lambda(c) \cdot |\Omega| &= \int_\Omega S_1(\vec{u}) - S_2(\vec{u},\vec{a},\vec{b})\, d\vec{x} \\ \phi'_\lambda(c) &= \frac{1}{|\Omega|}\int_\Omega S_2(\vec{u},\vec{a},\vec{b}) - S_1(\vec{u})\, d\vec{x} \qquad (15) \end{aligned}$$

The right hand side of eq. (15) also occurs in eq. (14) which can be reformulated as follows in order to be plugged in.

$$\frac{1}{|\Omega|}\int_{\Omega} S_2 - S_1 \, d\vec{x} = \Delta - T \quad \text{with} \quad \Delta = -\lambda \cdot \ln(\frac{1}{c} - 1)$$

$$\phi'_\lambda(c) = -\lambda \cdot \ln\left(\frac{1}{c} - 1\right) - T \tag{16}$$

To obtain ϕ_λ we integrate both sides of eq. (16) and get the following selection term with integration constant C.

$$\phi_\lambda(c) = \lambda\left(\ln(1-c) - c\cdot\ln\left(\frac{1}{c}-1\right)\right) - Tc + C \tag{17}$$

When chosing $C = T$ we can get a more intuitive formulation of the regularizer, using a cleverly tailored replacement ϕ for ϕ_λ.

$$\begin{aligned}\phi(c) = \frac{\phi_\lambda(c) + T\cdot(c-1)}{\lambda} &= \ln(1-c) - c\cdot\ln\left(\frac{1}{c}-1\right) \\ &= c\cdot\ln(c) + (1-c)\cdot\ln(1-c)\end{aligned} \tag{18}$$

$$\begin{aligned}R(\vec{u},c) = \int_\Omega \inf_{\vec{a},\vec{b}} \big[\, & c\cdot S_1(\vec{u}) + (1-c)\cdot\big(S_2(\vec{u},\vec{a},\vec{b}) + T\big) \\ & + \beta\cdot S_{\text{aux}}(\vec{a},\vec{b}) + \lambda\cdot\phi(c)\,\big]\, d\vec{x}\end{aligned} \tag{19}$$

In this representation the threshold parameter T appears in the convex combination together with S_2 and can be interpreted as an extra cost to be paid in order to use second order regularization. The sigmoid slope parameter λ now works as a weight for the selection term ϕ which has become independent of λ. In fact the selection term has simplified quite a bit and it can be seen that it is a symmetric function which is also illustarted in fig. 4. From the figure it can also be seen that ϕ is minimal for $c = \frac{1}{2}$ which can be interpreted as a prior on c for when the model is indecisive on regularization order. So by definition of ϕ neither of the regularizers is preferred, but due to the threshold T the descision is biased towards the first order regularization.

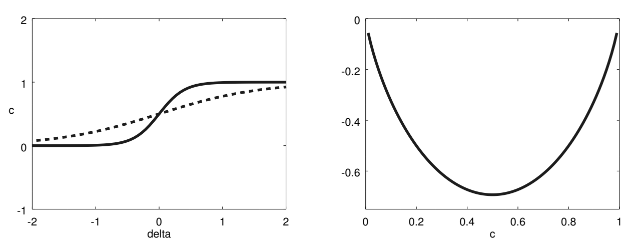

Figure 4: The left graph shows the weighting parameter c (eq. (14)) with respect to Δ, where Δ is the benefit of first over second order regularization biased by the threshold T. The solid line corresponds to $\lambda = 0.2$, the dotted line to $\lambda = 0.8$.
The right graph shows the selection term $\phi(c)$ (eq. (18)) which is axially symmetric to $c = \frac{1}{2}$.

5.2 Local Scheme

The previously introduced global scheme chooses regularization for the whole image domain, however, different parts of the scene may move differently so that it makes sense to allow for different regularization depending on the location. So instead of using a global weighting parameter c, it is replaced by a weighting function $c_{\text{local}}(\vec{x})$.

$$c_{\text{local}}(\vec{x}) = \frac{1}{1 + e^{-\Delta(\vec{x})/\lambda}} \quad \text{with} \quad \Delta(\vec{x}) = T + S_2 - S_1 \tag{20}$$

As a consequence Δ is now a spacially varying function as well, mapping to the benefit of first order regularization in a single pixel at $\vec{x}$, which allows the model to decide on order on a per pixel basis.

6 Exposition

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$$\sum_{j=1}^{z} j = \frac{z(z+1)}{2} \tag{21}$$

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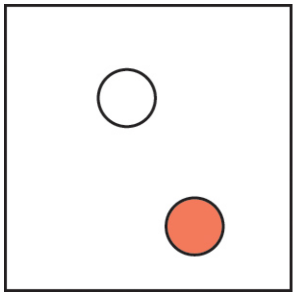

Figure 5: Beispielillustration.

Table 1: Vis Paper Acceptance Rate

Year	Submitted	Accepted	Accepted (%)
1994	91	41	45.1
1995	102	41	40.2
1996	101	43	42.6
1997	117	44	37.6
1998	118	50	42.4
1999	129	47	36.4
2000	151	52	34.4
2001	152	51	33.6
2002	172	58	33.7
2003	192	63	32.8
2004	167	46	27.6
2005	268	88	32.8
2006	228	63	27.6

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6.1 Mezcal Head

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6.1.1 Ejector Seat Reservation

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Rejected Ejector Seat Reservation Ut wisi enim ad minim veniam, quis nostrud exerci tation ullamcorper suscipit lobortis nisl ut aliquip ex ea commodo consequat. Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie

7 Conclusion

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