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NARODOWA STRATEGIA SPÓJNOŚCI



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„Image Processing and Computer Graphics”

Prezentacja multimedialna współfinansowana przez Unię Europejską w ramach Europejskiego Funduszu Społecznego w projekcie pt. „Innowacyjna dydaktyka bez ograniczeń - zintegrowany rozwój Politechniki Łódzkiej - zarządzanie Uczelnią, nowoczesna oferta edukacyjna i wzmacniania zdolności do zatrudniania osób niepełnosprawnych”



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Image Processing & Computer Graphics


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Contribution


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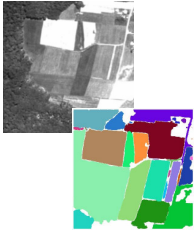




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Segmentation goal

- Segmentation partitions image into areas.
- Segmentation groups pixels in separate sets.
- Its goal is to find regions (areas) of interest for further analysis.



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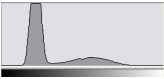
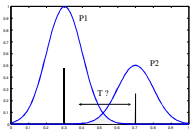


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Optimum thresholding

Suppose an image contains two intensity values m_1, m_2 combined with additive Gaussian noise $N(0,s)$ that appear in an image with apriori probabilities P_1 and P_2 correspondingly $P_1 + P_2 = 1$.

The task is to define a threshold level T that would minimise the overall segmentation error

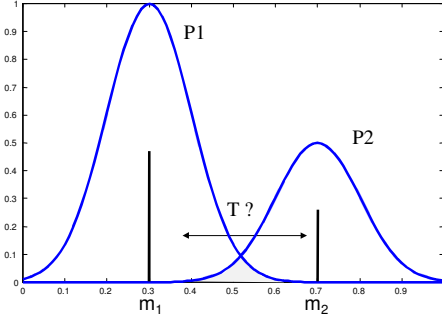



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Optimum thresholding



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Optimum thresholding

For $\sigma_1 = \sigma_2$ solution to this optimisation problem is the following:

$$T = \frac{m_1 + m_2}{2} + \frac{\sigma^2}{m_1 - m_2} \ln\left(\frac{P_2}{P_1}\right)$$

If $P_1 = P_2$, the optimal threshold is the average of the image intensities.

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Region based segmentation

The main idea in region-based segmentation techniques is to identify different regions in an image that have similar features (gray level, color, texture, etc.). There are two main region-based image segmentation techniques:

- region growing (merging)
- region splitting

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Region growing

In region growing the image is divided into **atomic regions** (e.g., pixels, templates). These “seed” points grow by appending to each point other points that have similar properties. The key problem lies in selecting proper criterion (predicate) for merging. A frequently used merging rule is:

*Merge two regions if they are „similar”
(in terms of a predefined features)*

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Region growing – general formulation

Let R represent the entire image. Segmentation may be viewed as a process that partitions R into N disjoint regions, R_1, R_2, \dots, R_N , such that:

- $\sum_{i=1}^N R_i = R$
- R_i is a connected region, $i = 1, 2, \dots, N$,
- $R_i \cap R_j = \emptyset$ for all i and j , $i \neq j$,
- $P(R_i) = TRUE$ for $i = 1, 2, \dots, N$,
- $P(R_i \cup R_j) = FALSE$ for $i \neq j$

where $P(R_i)$ is a logical predicate over the points in set R , and \emptyset is the empty set.

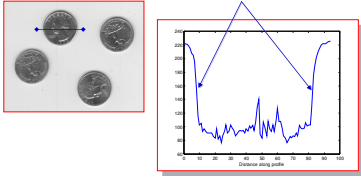
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Edge detection methods

Boundary based segmentation (edge detection)

Changes (or discontinuities) in an image amplitude are important characteristics of an image that carry information about object borders. Detection methods of image discontinuities are principal approaches to image segmentation and identification of objects in a scene. Local discontinuities in image intensity fall into three categories: points, lines, or edges



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Point detection



Point detection mask:

-1	-1	-1
-1	8	-1
-1	-1	-1

The point is rendered if:

$$|D| > T$$

where D is a similarity measure between the image and the template, and T is a non-negative threshold.

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Line detection

-1	-1	-1
2	2	2
-1	-1	-1

Horizontal

-1	2	-1
-1	2	-1
-1	2	-1



Vertical

-1	-1	2
-1	2	-1
2	-1	-1

+45°

2	-1	-1
-1	2	-1
-1	-1	2

-45°

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Line detection

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Edge detection

An edge
is the boundary between two regions with distinct gray-level properties.

Edges characterize the physical extent of objects thus their accurate detection plays a key role in image analysis and pattern recognition problems.

The main idea underlying most edge-detection techniques is the computation of a local derivative of an image.

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Edge detectors

Operators:

- Sobel
- Prewitt
- Roberts

Pairs of detectors
(gradient is a vector)

$$I_{\text{edges}}(i, j) = \sqrt{I_u^2(i, j) + I_v^2(i, j)}$$

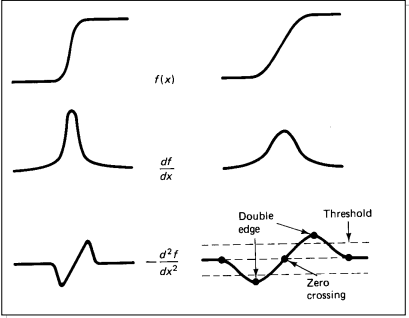
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Gradient operators (1D example)



$f(x)$
 $\frac{df}{dx}$
 $\frac{d^2f}{dx^2}$

Double edge, Threshold, Zero crossing

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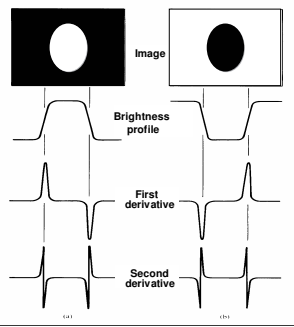
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Gradient operators (1D example)

the magnitude of the first derivative can be used to detect the presence of an edge in an image.

the sign of the second derivative can be used to determine whether an edge pixel is on the dark or light side of an edge.

the second derivative has zero crossing at the midpoint of a grey-level transition.



Image

Brightness profile

First derivative

Second derivative

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Gradient (2D)

Gradient (vector field)

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix}$$

Second order derivative „equivalents”:

- Gradient divergence
- Gradient curl (rotation)
- Laplacian vector field

Gradient's magnitude

$$\nabla f = \text{mag}(\nabla f) = \sqrt{G_x^2 + G_y^2} \approx |G_x| + |G_y|$$

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Vector calculus - Wikipedia, the free encyclopedia - Windows Internet Explorer

http://en.wikipedia.org/wiki/Vector_calculus

Go Search

Vector operations

Vector calculus studies various differential operators defined on scalar or vector fields, which are typically expressed in terms of the del operator (∇). The four most important operations in vector calculus are:

Operation	Notation	Description	Domain/Range
Gradient	$\text{grad}(f) = \nabla f$	Measures the rate and direction of change in a scalar field.	Maps scalar fields to vector fields.
Curl	$\text{curl}(\mathbf{F}) = \nabla \times \mathbf{F}$	Measures the tendency to rotate about a point in a vector field.	Maps vector fields to vector fields.
Divergence	$\text{div}(\mathbf{F}) = \nabla \cdot \mathbf{F}$	Measures the magnitude of a source or sink at a given point in a vector field.	Maps vector fields to scalar fields.
Laplacian	$\Delta f = \nabla^2 f = \nabla \cdot \nabla f$	A composition of the divergence and gradient operations.	Maps scalar fields to scalar fields.

A quantity called the **Jacobian** is useful for studying functions when both the domain and range of the function are multivariable, such as a change of variables during integration.

Theorems

Likewise, there are several important theorems related to these operators which generalize the fundamental theorem of calculus to higher dimensions.



Gradient - Wikipedia, the free encyclopedia - Windows Internet Explorer

http://en.wikipedia.org/wiki/Gradient

article discussion edit this page history

Gradient

From Wikipedia, the free encyclopedia

For the measure of steepness of a line, see Slope.
For other uses, see Gradient (disambiguation).

In vector calculus, the **gradient** of a scalar field is a vector field which points in the direction of the greatest rate of increase of the scalar field, and whose magnitude is the greatest rate of change.

A generalization of the gradient for functions on a Euclidean space which have values in another Euclidean space is the Jacobian. A further generalization for a function from one Banach space to another is the Fréchet derivative.

Contents [hide]

- Interpretations of the gradient
- Definition
- Expressions for the gradient in 3 dimensions
 - Example
- The gradient and the derivative or differential
 - Linear approximation to a function
 - The differential (exterior) derivative
 - Gradient as a derivative
 - Transformation properties
- Further properties and applications
 - Level sets
 - Conservative vector fields

In the above two images, the scalar field is in black and white, black representing higher values, and its corresponding gradient is represented by blue arrows.



Curl (mathematics) - Wikipedia, the free encyclopedia - Windows Internet Explorer

http://en.wikipedia.org/wiki/Curl_(mathematics)

Permanent link Cite this page

Definition

The curl of a vector field \vec{F} , denoted $\text{curl}(\vec{F})$ or $\nabla \times \vec{F}$, at a point is defined in terms of its projection onto various lines through the point. If \hat{n} is any unit vector, the projection of the curl of \vec{F} onto \hat{n} is defined to be the limiting value of a closed line integral in a plane orthogonal to \hat{n} as the path used in the integral becomes infinitesimally close to the point, divided by the area enclosed.

As such, the curl operator maps C^1 functions from \mathbb{R}^3 to \mathbb{R}^3 to C^0 functions from \mathbb{R}^3 to \mathbb{R}^3 .

Explicitly, curl is defined by^[1]

$$(\nabla \times \vec{F}) \cdot \hat{n} \stackrel{\text{def}}{=} \lim_{A \rightarrow 0} \frac{\oint_C \vec{F} \cdot d\vec{r}}{A}$$

Here $\oint_C \vec{F} \cdot d\vec{r}$ is a line integral around the area in question, and A is the magnitude of the area. If \hat{v} is an outward pointing normal to \hat{n} (see caption at right), then the orientation of C is chosen so that a vector \hat{c} tangent to C is positively oriented if and only if $\{\hat{n}, \hat{v}, \hat{c}\}$ forms a positively oriented basis for \mathbb{R}^3 (right-hand rule).

Intuitive Definition [edit]

Suppose the vector field describes the velocity field of a fluid flow (maybe a large tank of water or gas) and a small ball is located within the fluid or gas (the centre of the ball being fixed at a certain point). If the ball has a rough surface it will be made to rotate, by the fluid flowing past it. The rotation axis (oriented according to the right hand rule) points in the direction of the curl of the field at the centre of the ball, and the angular speed of the rotation is half the value of the curl at this point.

Even if all the flow lines are parallel, the ball can start spinning if the fluid moves past it faster on one side than the other.

Usage

In practice, the above definition is rarely used because in virtually all cases, the curl operator can be applied using some set of curvilinear coordinates, for which simpler representations have been derived.





Laplacian

Laplacian of a 2-D function $f(x,y)$ is a second derivative defined as:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

The Laplacian of a discrete image can be approximated by a difference equation:

$$\nabla^2 f \approx 4z_5 - (z_2 + z_4 + z_6 + z_8)$$



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Laplacian of a discrete image

0	-1	0
-1	4	-1
0	-1	0

-1	-1	-1
-1	8	-1
-1	-1	-1

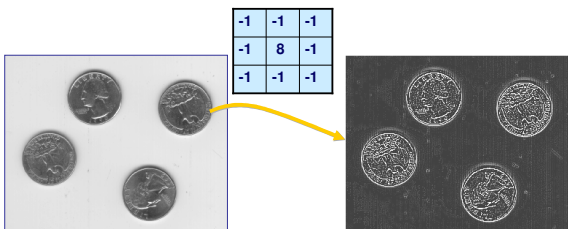


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Laplacian of a discrete image



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LoG (Laplacian of Gaussian)

A more suitable use of the Laplacian is in finding the location of edges using its *zero-crossing* property. This concept is based on convolving an image with the Laplacian of a 2-D Gaussian function of the form:

$$h(x, y) = \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

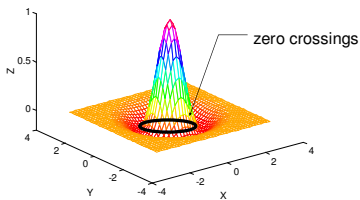
where σ is the standard deviation. Assume $r^2 = x^2 + y^2$. Then, the Laplacian of h with respect to r is:

$$\nabla^2 h = \left(\frac{r^2 - \sigma^2}{\sigma^4}\right) \exp\left(-\frac{r^2}{2\sigma^2}\right)$$

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LoG (Laplacian of Gaussian)

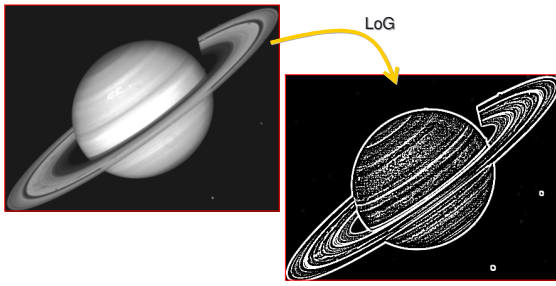


Laplacian of a 2-D Gaussian function for $\sigma=1$ (also called the Mexican hat function).

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LoG (Laplacian of Gaussian)



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The Laplacian of Gaussian

One of the first and also most common blob detectors is based on the Laplacian of the Gaussian (LoG). Given an input image $I(x, y)$, this image is convolved by a Gaussian kernel

$$g(x, y, t) = \frac{1}{2\pi t} e^{-(x^2 + y^2)/(2t)}$$

at a certain scale t to give a scale-space representation

$$L(x, y, t) = g(x, y, t) * f(x, y)$$

Then, the Laplacian operator

$$\nabla^2 L = L_{xx} + L_{yy}$$

is computed, which usually results in strong positive responses for dark blobs of extent \sqrt{t} and strong negative responses for bright blobs of similar size. A main problem when applying this operator at a single scale, however, is that the operator response is strongly dependent on the relationship between the size of the blob structures in the image domain and the size of the Gaussian kernel used for pre-smoothing. In order to automatically capture blobs of different (unknown) size in the image domain, a multi-scale approach is therefore necessary.

A straightforward way to obtain a multi-scale blob detector with automatic scale selection is to consider the scale-normalized Laplacian operator

$$\nabla_{norm}^2 L(x, y, t) = t(L_{xx} + L_{yy})$$

and to detect scale-space maxima/minima, that are points that are simultaneously local maxim/minima of $\nabla_{norm}^2 L$ with respect to both space and scale (Lindeberg 1998). Thus, given a discrete two-dimensional input image $I(x, y)$ a three-dimensional discrete scale-space volume $L(x, y, t)$ is computed and a point is regarded as a bright (dark) blob if the value at this point is greater (smaller) than the value in all its 26 neighbours. Thus, simultaneous selection of interest points (\hat{x}, \hat{y}) and scales \hat{t} is performed according to

$$(\hat{x}, \hat{y}, \hat{t}) = \operatorname{argmax}_{\min} \operatorname{local}_{(x, y, t)} (\nabla_{norm}^2 L(x, y, t))$$

Note that this notion of blob provides a concise http://en.wikipedia.org/wiki/Blob_detection



Laplacian of Gaussian (LoG)

As Laplace operator may detect edges as well as noise (isolated, out-of-range), it may be desirable to smooth the image first by convolution with a Gaussian kernel of width σ

$$G_\sigma(x, y) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

to suppress the noise before using Laplace for edge detection:

$$\Delta[G_\sigma(x, y) * f(x, y)] = [\Delta G_\sigma(x, y)] * f(x, y) = LoG * f(x, y)$$

The first equal sign is due to the fact that

$$\frac{d}{dt}[h(t) * f(t)] = \frac{d}{dt} \int f(\tau) h(t-\tau) d\tau = \int f(\tau) \frac{d}{dt} h(t-\tau) d\tau = f(t) * \frac{d}{dt} h(t)$$

So we can obtain the Laplacian of Gaussian $\Delta G_\sigma(x, y)$ first and then convolve it with the input image. To do so, first consider

$$\frac{\partial}{\partial x} G_\sigma(x, y) = \frac{\partial}{\partial x} e^{-(x^2 + y^2)/2\sigma^2} = -\frac{x}{\sigma^2} e^{-(x^2 + y^2)/2\sigma^2}$$

and

$$\frac{\partial^2}{\partial x^2} G_\sigma(x, y) = \frac{\partial^2}{\partial x^2} e^{-(x^2 + y^2)/2\sigma^2} = \frac{1}{\sigma^4} e^{-(x^2 + y^2)/2\sigma^2} - \frac{x^2 - \sigma^2}{\sigma^4} e^{-(x^2 + y^2)/2\sigma^2}$$

<http://fourier.eng.hmc.edu/e161/lectures/gradient/node10.html>



The determinant of the Hessian

By considering the scale-normalized determinant of the Hessian, also referred to as the *Monge-Ampère operator*,

$$\det HL(x, y, t) = t^2 (L_{xx} L_{yy} - L_{xy}^2)$$

where HL denotes the Hessian matrix of L and then detecting scale-space maxima of this operator one obtains another straightforward differential blob detector with automatic scale selection which also responds to saddles (Lindeberg 1998)

$$(\hat{x}, \hat{y}, \hat{t}) = \operatorname{argmax}_{\min} \operatorname{local}_{(x, y, t)} (\det HL(x, y, t))$$

The blob points (\hat{x}, \hat{y}) and scales \hat{t} are also defined from an operational differential geometric definitions that leads to blob descriptors that are invariant with translations, rotations and rescalings in the image domain. In terms of scale selection, blobs defined from scale-space extrema of the determinant of the Hessian (DoH) also have slightly better scale selection properties under non-Euclidean affine transformations than the more commonly used Laplacian operator (Lindeberg 1998). In simplified form, the determinant of the Hessian computed from Haar wavelets is used as the basic interest point operator in the SURF descriptor (Bay et al 2008) for image matching and object recognition.

The hybrid Laplacian and determinant of the Hessian operator (Hessian-Laplace)

A hybrid operator between the Laplacian and the determinant of the Hessian blob detectors has also been proposed, where spatial selection is done by the determinant of the Hessian and scale selection is performed with the scale-normalized Laplacian (Mikolajczyk and Schmid 2004).

$$(\hat{x}, \hat{y}) = \operatorname{argmax}_{\min} \operatorname{local}_{(x, y)} (\det HL(x, y, t))$$

$$\hat{t} = \operatorname{argmax}_{\min} \operatorname{local}_{(x, y, t)} (\nabla_{norm}^2 L(x, y, t))$$

This operator has been used for image matching, object recognition as well as texture analysis.

Affine-adapted differential blob detectors

The blob descriptors obtained from these blob detectors with automatic scale selection are invariant to translations, rotations and uniform rescalings in the spatial domain. The images that constitute the input to a computer vision system are, however, also subject to perspective distortions. To obtain blob descriptors that are more robust to perspective transformations, a natural approach is to



Optical flow - Wikipedia, the free encyclopedia - Windows Internet Explorer

WIKIPEDIA The Free Encyclopedia

Optical flow

From Wikipedia, the free encyclopedia

Optical flow or optic flow is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene. [1][2] Optical flow techniques such as motion detection, object segmentation, time-to-collision and focus of expansion calculations, motion compensated encoding, and stereo disparity maps.

Contents [hide]

- Estimation of the optical flow
 - Methods for determining optical flow
 - Uses of optical flow
 - References
 - External links

Estimation of the optical flow [edit]

Sequences of ordered images allow the estimation of motion as either instantaneous image velocities or discrete image displacements [3] Fleet and Weiss provide a tutorial introduction to gradient based optical flow. [4] John L. Baron, David J. Fleet, and Steven Szeliski provide a performance analysis of a number of optical flow techniques. It emphasizes the accuracy and density of measurements [5].

The optical flow methods try to calculate the motion between two image frames which are taken at times t and $t + \Delta t$ at every voxel position. These methods are called differential since they are based on local Taylor series approximations of the image signal, that is, they use partial derivatives with respect to the spatial and temporal coordinates.



Optical flow - Wikipedia, the free encyclopedia - Windows Internet Explorer

Methods for determining optical flow [edit]

- Phase correlation – inverse of normalized cross-power spectrum
- Block-based methods – minimizing sum of squared differences or sum of absolute differences, or maximizing normalized cross-correlation
- Differential methods of estimating optical flow, based on partial derivatives of the image signal and/or the sought flow field and higher-order partial derivatives, such as:
 - Lucas-Kanade method – regarding image patches and an affine model for the flow field
 - Horn-Schunck method – optimizing a functional based on residuals from the brightness constancy constraint, and a particular regularization term expressing the expected smoothness of the flow field
 - Buxton-Buxton method – based on a model of the motion of edges in image sequences [6]
 - Black-Jepson method – coarse optical flow via correlation [6]
 - General variational methods – a range of modifications/extensions of Horn-Schunck, using other data terms and other smoothness terms
- Discrete optimization methods – the search space is quantized, and then image matching is addressed through label assignment at every pixel, such that the corresponding deformation minimizes the distance between the source and the target image [10]. The optimal solution is often recovered through min-cut max-flow algorithms, linear programming or belief propagation methods.

Uses of optical flow [edit]

Motion estimation and video compression have developed as a major aspect of optical flow research. While the optical flow field is superficially similar to a dense motion field derived from the techniques of motion estimation, optical flow is the study of not only the determination of the optical flow field itself, but also of its use in estimating the three-dimensional nature and structure of the scene, as well as the 3D motion of objects and the observer relative to the scene.

Optical flow was used by robotics researchers in many areas such as: object detection and tracking, image dominant plane extraction, movement detection, robot navigation and visual odometry [11].

The application of optical flow includes the problem of inferring not only the motion of the observer and objects in the scene, but also the structure of objects and the environment. Since awareness of motion and the generation of mental maps of the structure of our environment are critical components of animal (and human) vision, the conversion of this innate ability to a computer capability is similarly crucial in the field of machine vision [12].



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Block matching

- MAD – Mean Absolute Difference
- SAD – Sum of Absolute Differences
- MI – Mutual Information
- NCC – Normalized Cross-Correlation

$$MAD(x, y) = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N |I_{image}(x + m - \frac{M}{2}, y + n - \frac{N}{2}) - I_{block}(m, n)|$$

image

block

MAD

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Segmentation from motion

- Divide video frame (n) into blocks,
- Calculate MAD functions of all the blocks by matching them with the next frame (n+1),
- For each block calculate vector from block coordinates to MAD maximum corresponding with the block,
- Find high magnitude vectors.

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Deformable models

Deformable models

```

graph TD
    A[Deformable models] --> B[Nonparametric]
    A --> C[Parametric]
    
```

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The screenshot shows a browser window with the URL [http://en.wikipedia.org/wiki/level_set_method](http://en.wikipedia.org/wiki/Level_set_method). The article title is "Level set method". The text describes it as a numerical technique for tracking interfaces and shapes. It mentions the advantage of not needing to parameterize shapes and its use in modeling time-varying objects like an inflating airbag. A "Contents" table lists sections: 1 Level set function, 2 The level set equation, 3 History, 4 See also, 5 References, 6 External links. The "Level set function" section is partially visible, defining the level set $\Gamma = \{(x, y) | \varphi(x, y) = 0\}$ and mentioning the auxiliary function φ . An image shows a sequence of shapes: a blob, a dumbbell, a circle, and a point, illustrating the evolution of a level set.

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Active contour (parametric model)

$$E_S = \sum_s [E_f(\mathbf{v}(s)) + E_p(\mathbf{v}(s))]$$

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Active contour in 3D (deformable surface)

$$E_S = \iint_{\Omega} [E_f(\mathbf{v}(s)) + E_p(\mathbf{v}(s))] ds$$

$$E_f = \tau \left[\left| \frac{\partial \mathbf{v}}{\partial t} \right|^2 + \left| \frac{\partial \mathbf{v}}{\partial j} \right|^2 \right] + \rho \left[\left| \frac{\partial^2 \mathbf{v}}{\partial t^2} \right|^2 + 2 \left| \frac{\partial^2 \mathbf{v}}{\partial t \partial j} \right|^2 + \left| \frac{\partial^2 \mathbf{v}}{\partial j^2} \right|^2 \right]$$

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http://www.elestat.p.lodz.pl/ima/bade_en.html

Plotr M. Szczypiński

ACTIVE CONTOUR

Active contour is a mathematical model of deformable curve made up of abstract, elastic material. It is used for computer image analysis, for detection of object boundary that is presented in the computer image.

At the beginning of analysis, active contour (that has a simple, arbitrary chosen shape) is placed on the surface of the image. Then process of matching starts, which displace and deforms active contour to fit it to the shape of objects boundary.

Process of active contour matching performed for ultrasound image of a human heart. The purpose of the analysis is to detect a shape of left ventricle.

Some additional information on active contour may be found on the [Publications page](#).

DEFORMABLE MODEL

Deformable (elastic) model is mathematical model for computer image analysis. It may be used for object recognition, for finding objects co-ordinates, size and orientation. In case of object in motion, deformable model may be used for tracking its movement.

Deformable model looks like a grid that is placed on the surface of computer image. At the first step, not deformed grid is placed on the surface of image presenting a reference (model) object. During this step, the information on local image features is stored at every node of a grid. We can say that grid nodes have reference object looks like. In the next step the grid is placed on a surface of the image, which presents an object to be analysed. Then process of matching starts, which displace and deforms deformable model's grid to fit a stored image of reference object to the object being analysed.

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