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Symmetry Signatures for Image-Based Applications in Robotics

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1. Introduction

The robots that are to find their way in our future households and everyday lives necessarily have to be mobile and self-dependent. For such autonomous systems it becomes more and more important to efficiently process the incoming data and to thereby eradiate what we might call "intelligent behaviour".

While intelligence in terms of plans and goals are abstract metaphors of each robot's decision process, the perception of the local environment has to be a central issue. Dealing with this demand in the context of intelligent systems shows plainly what sophisticated human visual perception is like. The creators and developers of artificial systems therefore build up a construction kit with construction blocks that try to represent the reproduction of cognitive perception mechanisms by machine algorithms.

In this chapter, we will show how a construction block for symmetry perception can be added to this set. The main issues discuss three layers that describe this block from its origin of biological motivation up to its application for intelligent systems:

1. Symmetry as a Feature: The first layer addresses the basic motivation of symmetry as a feature. Therefore, symmetry references to diverse domains are given and new methods developed that provide description and application of symmetry as an image feature. These include two main symmetry measures that offer a variety of symmetry properties for higher-level image processing tasks.

2. Regional Symmetry Features: The second layer proceeds to application in relation to modern regional image features. The three steps of detection, description and robust matching of regional symmetry features form the necessary links between the basic motivation and the practical application of symmetry. Symmetry features are evaluated and compared to state-of-the-art features considering their robustness w.r.t. common image transformations.

3. Integration and Application: A practical example from the area of mobile robot navigation is proposed in the third layer to demonstrate the capability of the developed symmetry features in applications. For this purpose, the mobile service robot TASeR from the working group of Technical Aspects of Multimodal Systems (University of Hamburg, Germany) is used. The application provides the links to higher-level construction blocks from the set of visual object analysis and robot navigation.

The main issue of this chapter will focus on a conclusion of our work on a fundamental analysis of symmetry as an image feature, followed by a framework on the development of a robust visual symmetry feature detector and on the implementation of symmetry in robot applications. We motivate our work in section 2. In section 3, we show our work on finding symmetry measures valuable for our goal of robotic applications. Section 4 describes the implementation of the developed symmetry measures into a regional feature detector and its evaluation. We propose some preliminary work on exemplary integrating those regional features into robotic image processing for egomotion classification in section 5, before we conclude this chapter in section 6.

2. Motivation

Nowadays, robots are not only meant to sort and stack parcels in unenlivened storage depots. They are supposed to wash dishes, to lead through museum halls or even to play soccer in interaction with humans. For these tasks, a robot must be able to act mobile and self-dependent. It must adapt to its changing environment instead of letting humans adapt a constant environment for the robot. An inflexible model of the world is useless in a world of motion and dynamics. Robots thus have to be equipped with methods that allow them to build their own world model to localize within. They should be able to handle in dynamic or unknown environments by constructing, adapting and expanding their models of the world with a large degree of autonomy. However, the interaction in a world necessarily starts with the perception of things or objects inside. In many applications of our field of research, the human visual system gives a wide inspiration to the solution of common robotic problems and tasks, e.g. distance estimation to objects, object and situation recognition and localisation. We can also observe that a robot's sensor configuration is both depending on the application and on the financial means of constructors, developers and customers. A camera has the advantages of becoming versatile and cheap visual sensor over the last years and of being a system that is very close to our own human visual perception. In the work presented here, we focus on the camera as the only sensor.

If we restrict on visual data only, the problem of selecting special visual features comes up, as images are high-dimensional and thus complex to process. Additionally, images are highly sensitive to unpredictable interferences like rotation, scaling and occlusion of objects, illumination influence, perspective warp and viewpoint change. In (Jepson & Richards, 1993), the meaning of a "good" visual feature that separates the core of information from the clutter basically depends on the application itself. Some other definitions suppose that an image feature is a

- local, meaningful, detectable part of an image (Truco & Verri, 1998),
- a distinguishing primitive characteristic or attribute of an image (Pratt, 2001),
- or a simple environmental measurement serving as a "cue" for inferring complex world properties in structured environments (Taraborelli, 2003).

Each of the definitions shows that image features are something that really point out the compact core of the whole visual data. In our work, we define a good image feature as being robust to the above mentioned transformations in dynamic real-world environments. Additionally, we focus on natural features that can be found in a lot of "untouched" environments, i.e. without artificial landmarks.

Though all imaginable visual features are numerous and manifold in type, they can be divided into one of three main classes belonging to their focus. Common *global features* that describe general properties of an entire image scene are rather inappropriate for the task of visual scene interpretation. While images of single objects can be generalized easily by simple global attributes, e.g. size, colour or texture, it is more difficult to find stable and repeatable features for conglomerate scenes. However, global features give very compact representations of significant image properties.

Many higher-level tasks like scene exploration or object classification and object tracking in complex scenes are therefore grounded on *local features*. Being related to human visual perception, local visual features like edges and corners give clues for efficient scene exploration and allow focusing on well-located interest points. The Scale-Invariant Feature Transform (Lowe, 2004) and the Harris-Laplacian (Mikolajczyk & Schmid, 2004) are popular methods of local feature detection, approaching robustness to rotation and scale. As the exploration of invariant features is an active field of research, well-elaborated comparisons of various local feature detectors and descriptors concerning a set of common transformations have been published (Mikolajczyk & Schmid, 2004; Schmid et al., 2000; Mikolajczyk & Schmid, 2005).

Due to the different characteristics of global and local features, some applications benefit from the combination of both approaches into *regional features*, where a region is defined as an arbitrary subset of the image. The extraction of Maximally Stable Extremal Regions (Matas et al., 2004) highlights the advantage of region-based detectors that produce both sparse and robust features particularly covariant to viewpoint change and affine transformations.

If we consider these issues of different natural visual features, we find local features like edges or corners, regional features like colour or intensity blobs, or global features like colour histograms in the literature. A rather unnoticed type of feature to use in robotic applications is symmetry, though symmetry is present everywhere in our everyday's life. Many objects of our world show a high degree of some symmetric property and humans are usually surrounded with symmetric objects. Plants and animals grow up in a somehow symmetric manner. But even in many other domains like mathematics, art, architecture or manifacturing, symmetry plays a major role.

Let some psychological cites from (Locher & Nodine, 1989) describe the high influence of symmetry on human visual perception:

- Symmetry is a property of a visual stimulus which catches the eye in the earliest stages of vision.
- Most perceptual theories assume that the eye-brain system uses the axis of symmetry as an anchoring point for visual exploration and analysis.

Symmetry comes along with attention and interest, which are supposed to be necessary for a useful natural image feature. We claim that therefore symmetry is worth a view on being used as a feature in the context of robot vision. In the next section, we will start by asking the question on "how can we receive a description of symmetry from the visual data?".

3. Symmetry as a Feature

As mentioned above, symmetry is a fundamental feature that is evaluated throughout several domains, e.g. architecture, art and nature (see Figure 1). Many aspects that concentrate on nature and mathematics are discussed in the book "Fearful Symmetry: Is

God a Geometer?" (Stewart & Golubitsky, 1992). It has been shown in the biological domain that some animals prefer mates that outperform by their symmetric appearance (Enquist & Arak, 1994; Kirkpatrick & Rosenthal, 1994), or that doves are able to distinguish between symmetric and asymmetric patterns (Delius & Nowak, 1982). A very good introduction to several types and appearances of general symmetry can be found in the book "Symmetry – A Unifying Concept" (Hargittai & Hargittai, 1994).

3.1 Definition of Symmetry

Besides this introduction, we also find descriptions of various types of symmetry in that work (Hargittai & Hargittai, 1994). Each type of symmetry can be assigned to a corresponding action that fulfills the basic property of symmetry: keeping the shape after having performed the action. Thus, we can reflect shapes along an axis that are mirror-symmetric, or rotate shapes that are rotationally symmetric, or even shift shapes that are translationally symmetric, without changing their shape. Here, we focus on the first two types of symmetries by giving the following definitions:

- Reflectional symmetry: A shape is symmetric w.r.t. the reflection along an axis. Reflecting the shape along this axis does not result in a change of its appearance. Special cases of reflectional symmetry are horizontal (reflection along a horizontal axis) and vertical mirror-symmetry (reflection along a vertical axis).
- Rotational symmetry: A shape is symmetric w.r.t the rotation about a point and a certain angle α. Rotating the shape at the point about α does not result in a change of its appearance. A shape is n-times rotational symmetric with $n = 2\pi/\alpha$.

These definitions are leaned against more detailed and more general definitions of two-dimensional symmetry types by Zabrodsky et al. (Zabrodsky et al., 1995), which are based on exact invariance. However, almost no object of our world shows invariant symmetry properties from this point of view. For example, faces are highly symmetric, but both halves of one face are never exactly the same. Therefore, we differ our above definitions by using the term "change of appearance". A common face is thus reflectional symmetric, as the reflection does not change perception or appearance for the viewer. Following this definition, we find that or world consists of many symmetric objects.

3.2 Symmetry in Human Perception

How the existence of symmetry influences the human visual system and how this is used for visual scene exploration, was evaluated in psychophysical experiments (Locher & Nodine, 1989). As an important result of those experiments it was shown that especially reflectional symmetries and their orientations are of significant importance for human vision. Eye-tracking experiments show that humans quickly detect and take advantage of horizontal and vertical symmetries. Figure 1 gives two samples of such visual explorations. While the viewer has fully explored the asymmetric shape on the left hand side, the focus clearly concentrates on just one half of the symmetric shape on the right. Hereby, we get a clue that the human eye is able to detect and use symmetry as a visual anchoring point for visual exploration of objects and scenes. Palmer and Hemenway (Palmer & Hemenway, 1978) consider the time of detection of arbitrarily skewed symmetric shapes in similar experiments. They conclude that vertical reflective symmetry is very often and more quickly detected than horizontal reflective symmetries, which is better than arbitrarily skewed reflective symmetries.

Those two references are exemplary for others that also motivate symmetry as a visual feature from the biological and psychophysical point of view (Barlow & Reeves, 1979; Csathó et al., 2003; Ferguson, 2000; Tyler, 1994).

3.3 Symmetry in Computer Vision

Besides its influence on human visual perception, symmetry has also been investigated in computer vision. There are some references that motivate symmetry as a feature in very versatile tasks (Ferguson, 2000; Liu, 2000; Reisfeld et al., 1995; Zabrodsky, 1990). Early work in the area of symmetry axis extraction for object description, like the Symmetry Axis Transform (Blum & Nagel, 1978) and the Smoothed Local Symmetries (SLS) (Brady & Asada, 1984), are very related to the Medial Axis Transform (MAT) offering main axes of a shape. The idea of using symmetry as a feature has been advanced over the last decades. In the following, some recent and related work is referenced.
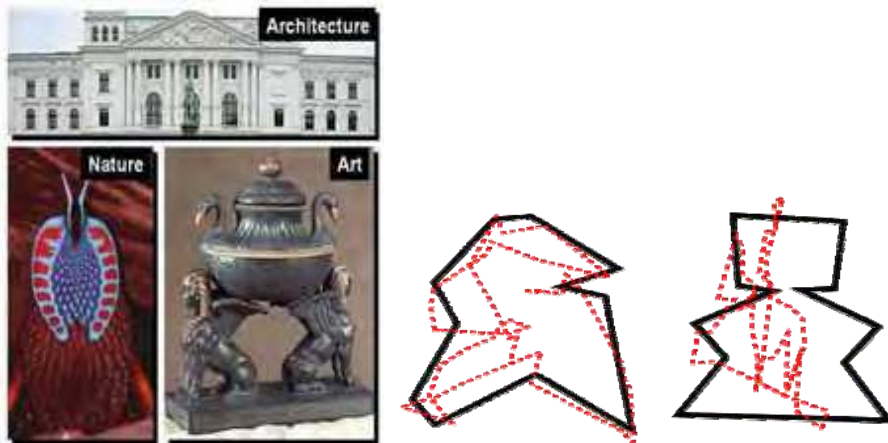

Figure 1. Left: Examples for symmetric structures in architecture, nature and art. Right: Visual explorations both on an asymmetric and a symmetric shape. The path of visual focus covers the whole shape for the asymmetric shape, but only one half of the symmetric shape

Sun (Sun, 1995) and Sun & Si (Sun & Si, 1999) present a fast algorithm to detect the symmetry axis of a shape by gradient histograms. A similar approach analyzing an energy function of the input image is proposed by Scognamillo et al. (Scognamillo et al., 2003). The task of these methods is to detect the main symmetry axis of one shape, thus only images with a single object on a uniform background are useful. An application to symmetry as a feature in an arbitrary scene would therefore need prior segmentation.

Reisfeld et al. (Reisfeld et al., 1995) define a generalized symmetry transform that uses symmetry to extract regions-of-interest in a scene. The two-dimensional operator both includes symmetry as also gradient information. Regions that show a high degree of symmetry, but low contrast, e.g. walls, are therefore not extracted. Di Gesù and Valenti present the Discrete Symmetry Transform (DST) which is speeded up by the selection of non-uniform image regions (Di Gesù & Valenti, 1995). The resulting symmetry image is used for several tasks of face recognition, image segmentation and object classification as also motion analysis (Di Gesù & Valenti, 1996). These approaches suffer from the generality

which causes higher effort in calculation time and parametrization. Similar results using symmetry as a detector of interest have been shown by analyzing frequency components of an image (Kovesi, 1997).

Chetverikov (Chetverikov, 1999; Chetverikov, 2003) analyzes the surrounding of each image point with regard to its anisotropy. Based on this result, a symmetry structure is calculated that represents symmetric texture orientation. The extracted feature thereby describes the texture and the image, respectively, as a whole. Liu et al. (Liu et al., 2004) describe patterns considering their symmetry properties, including translational symmetries. Regions that even correspond with regard to their structure of symmetric shape after perspective warp are deeply investigated by Tuytelaars et al. (Tuytelaars et al., 2003). However, these afford a number of pre-processing steps that influence the run-time of each feature detection.

Face recognition based on symmetry description is found in a model-based work by Zabrodsky et al. (Zabrodsky et al., 1993; Zabrodsky et al., 1995). Another model-based approach to segment objects from the visual data by symmetry is proposed by Liu et al. (Liu et al., 1998). Johansson et al. (Johansson et al., 2000) detect rotational symmetries by particularly defined rotational operators, while Loy and Zelinsky (Loy & Zelinsky, 2003) present an efficient and real-time capable feature detector based on radial symmetries.

We find that all these approaches differ both in the methods applied and the results, though all of them handle the problem of detecting symmetries in the visual data. Some describe symmetry properties for a pre-segmented object (Chetverikov, 1999; Liu et al., 2004; Sun, 1995) and are thereby inadequate for the extraction of feature points from cluttered scenes. Some include reflective symmetries of arbitrary orientation (Chetverikov, 1999; Di Gesù & Valenti, 1995; Di Gesù & Valenti, 1996; Kovesi, 1997; Reisfeld et al., 1995; Sun, 1995; Zabrodsky et al., 1995), offer methods to extract rotational symmetries (Johansson et al., 2000; Loy & Zelinsky, 2003; Zabrodsky et al., 1995) or use pre-processing steps (Liu et al., 2004; Tuytelaars et al., 2003) and thereby need additional effort in computing time.

For our scenario, we prefer an approach that extracts symmetric features from the raw visual data without such pre-processing steps, similar to the work by Reisfeld et al. (Reisfeld et al., 1995) and Di Gesù and Valenti (Di Gesù & Valenti, 1995; Di Gesù & Valenti, 1996). A time-line of the mentioned literature is presented in Table 1.

The diagonal line highlights the trend towards detection of very general, different and complex descriptions of symmetry in computer vision. However, a real-time application in robotic systems suffers from this evolution, as more complex algorithms need more processing time.

We found that most image processing operators available for our needs of bilateral symmetry detection in cluttered scenes have the crucial demerit of being large and complex. In our first approach, we therefore proposed a simple, fast and compact operator to extract the regions of interest from images (Huebner, 2003). The psychophysically motivated simple symmetry operator detects horizontal and vertical reflective symmetries only. Resulting symmetry images offer multiple feature extraction methods.

In particular, binary images derived from symmetry axis detection are interesting for further image processing steps. As we show in the next section, the fast operator can be applied to arbitrary images without prior adaptation and without thresholds. The only parameters to specify are the size of the operator mask and the resolution of symmetry data.

Approach key	Method	Reflective	Rotational	Translational	Number of features	Type of features
Blum & Nagel (1978)	SAT	●			b	Object skeleton
Brady & Asada (1984)	SLS	●			b	Object skeleton
Reisfeld et al. (1995)	CF	●			m × n	Symmetry values
Di Gesù et al. (1995)	CF	●			m × n	Symmetry values
Sun (1995)	CF	●			1	Main symmetry axis
Zabrodsky et al. (1995)	MOD	●	●		b	Reconstructions
Kovesi (1997)	FQ	●			m × n	Symmetry values
Liu et al. (1998)	MOD	●			b	Symmetry segments
Chetverikov & Jankó (1999)	CF	●			1	Regularity values
Cross & Hancock (1999)	CF	●			b	Main symmetry axes
Sun & Si (1999)	CFQ	●			b	Symmetry axis points
Johansson et al. (2000)	CF		●		m × n	Symmetry values
Loy & Zelinsky (2003)	CF		●		m × n	Symmetry values
Scognamillo et al. (2003)	CFQ	●			1	Main symmetry axis
Tuytelaars et al. (2003)	MOD	●		●	b	Symmetry groups
Liu et al. (2004)	MOD	●	●	●	b	Classification
Mellor & Brady (2005)	CFQ	●	●		m × n	Symmetry values

Table 1. Time-line of selected approaches on symmetry detection. CF = Convolution Filter. FQ = Frequency analysis (Fourier / Wavelet Transform). CFQ = Hybrid CF/FQ. MOD = model-base

3.4 A Fast One-Dimensional Symmetry Operator

The psychological experiments described in section 3.2 show that vertical and horizontal reflective symmetries are most important for human vision. Based on these results, only these two types were considered for our symmetry approach. This selection proves even more effective if we take into account that it is not necessary to perform any interpolation or to use trigonometric functions, since digital images consist of horizontal and vertical arrays of pixels. Therefore, only pixels in the same image row $R = [p_0, p_{w-1}]$ have to be used for the detection of vertical symmetry for a given pixel $p_i \in R$, where w is is the width of the image. The same holds for horizontal symmetry, considering only one column of the image.

A further requirement of robot vision is the processing of real images. Because of the presence of distortion in real images, an operator that detects exact symmetry will fail and produce erroneous symmetry images. Therefore, we propose the following qualitative symmetry operator based on a normalized mean square error function:

$$S(p_i, m) = 1 - (c \cdot m)^{-1} \sum_{j=1..m} \sigma(j, m) \cdot g(p_{i-j}, p_{i+j})^2, \qquad (1)$$

where m>0 is the size of the neighbourhood of p_i along the direction perpendicular to the axis of symmetry. The symmetry value of p_i shall be detected with respect to this axis. The complete number of pixels considered is 2m. c is a normalization constant which depends

on the colour space used and on $\sigma(j, m)$, which is a radial weighting function. The difference between two opposing points p_{i-j}, p_{i+j} is determined by a gradient function $g(p_{i-j}, p_{i+j})$, which typically is the Euclidian distance of the corresponding colour vectors. A few example results are presented in Figure 2, demonstrating that the choice of m is important for the performance of the algorithm. Setting m to a low value works out well for the symmetry axes of small objects, while those of bigger objects are enlarged. However, a large value m is better in detecting the symmetry axes of bigger objects. Note that the border regions of the images (left and right for vertical symmetry) are influenced strongly by the effect of fading if the operator reaches out of the image, but symmetry axis points (maxima of the values) are quite stable and independent of m. However, for this operator and for other techniques from the literature, a symmetry value for an image point is detected by a static operator covering a surrounding region around that point. These operators return relative values, i.e. qualities, of symmetry that describe symmetry as low or high inside a pre-determined, fixed region. We call these approaches *qualitative* or *strength-based*, as a quality of symmetry is their output. Results are depending on the operator size chosen and thus not comparable if two different sizes have been used for symmetry feature extraction.

Figure 2. Example image (left). Vertical symmetry image calculated with small operator (m = 10; centre) and with large operator (m = 50; right). Brightness corresponds to symmetry.

3.5 Quantitative Symmetry Extraction using Dynamic Programming

Having uncovered these disadvantages of qualitative operators, we claim that it is more relevant to get *quantitative* or *range-based* information about the size of symmetry instead of its degree. We have therefore proposed a novel approach to symmetry extraction based on Dynamic Programming (Huebner et al., 2005), which we briefly describe in this section.

To keep the motivation of psychophysical work on symmetry perception (Locher & Nodine, 1989; Palmer & Hemenway, 1978), we still restrict our symmetry detection to horizontal and vertical symmetry detection, i.e. reflection with respect to a horizontal or vertical axis. Using this restriction, the problem states to estimate the range around an image point in its row or column in which symmetry is still detectable, i.e. the assignment of opposing points is linear and not erroneous.

The assignment of points is therefore seen as an optimization problem to find the best correspondence between the two opposing patterns. Dynamic Programming offers the global optimum for such problems, including the assumption that the order of pattern elements is kept. See the example in Figure 3.

The example shows two patterns $R = R_0,...,R_4$ and $L = L_0,...,L_4$ for which the best correspondence between their elements shall be found. The solution of this problem is equal to finding the best path in a two-dimensional search space spanned by L and R (Ohta & Kanade, 1985). Each path ranging from (R_0, L_0) to (R_{rmax}, L_{lmax}) inside this search space describes a possible mapping of feature points, as long as the order of elements is kept. This

property is only ensured by path elements reaching from one cell to the right, the top-right or the top neighbouring cell in the search space. The optimal path can then be found by Dynamic Programming starting from point (R_0, L_0), using simple error measures (Žganec et al., 1993), as can be seen in Figure 4.

Note that the structure of the path and the overall costs are dependent on the patterns' symmetric correspondence. As the example shows, high symmetry of the patterns results in a diagonal path and low costs. In contrast, the comparison of asymmetric shapes will result in a non-linear path and high costs.
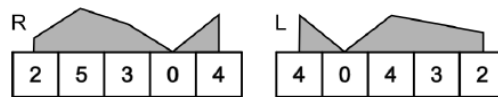
Figure 3. Example patterns to calculate range-based symmetry by Dynamic Programming

$$C(l,r) = \qquad (2)$$
$$= \min(C_1(l,r), C_2(l,r), C_3(l,r)),$$

$$C_1(l,r) = C(l-1, r) + W_1 T(l,r),$$
$$C_2(l,r) = C(l, r-1) + W_2 T(l,r),$$
$$C_3(l,r) = C(l-1, r-1) + W_3 T(l,r),$$
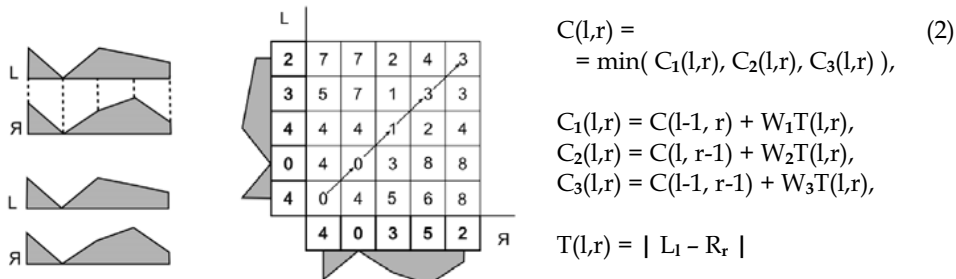
$$T(l,r) = | L_l - R_r |$$

Figure 4. Right: Error measures that are used for Dynamic Programming. Centre: Symmetric patterns' search space including costs and corresponding mapping path ($W_i = 1$). Left: Resulting (linear) correspondences

Practically, it is easier to handle the cost development on the optimal path than to evaluate the path structure. Therefore, our final algorithm efficiently searches optimal paths until a cell (l, r) exceeds a given threshold T. The hereby acquired indices l and r serve as a measure of symmetry. Note that the environment s composed of l and r can be treated intuitively as the size of the symmetric region s = l + r around the considered image point. A search space calculation of an asymmetric pattern is interrupted by exceeding the error T. In this case, l and r are small, as well as the symmetry measure s. On the other hand, a symmetric pattern like the one above results in an optimal path that leads along the search space quite diagonally with small error, which justifies a high symmetric value s.

While this just briefly points out the idea of using a Dynamic Programming approach for symmetry description, we have worked out and optimized this approach as the Dynamic Programming Symmetry (DPS) algorithm in (Huebner et al., 2005). As a main achievement of DPS in contrast to qualitative symmetry operators, the disadvantages of a-priori-sized operators are avoided. In addition, a range-based, comparable description of symmetry is returned instead of a relative measure that describes symmetry as high or low only.

4. Regional Symmetry Features

Based on the symmetry components of qualitative and quantitative symmetry, it is an important task to make symmetry features comparable, stable and repeatable in different

images. Robust detection of features is a crucial task for applications that deal with visual information. Image data is high-dimensional, complex and particularly sensitive to a multitude of changes which are mostly unpredictable and may greatly influence the image representation of one and the same object or scene. Therefore, a good feature detection is strongly required in dynamic and unrestricted real world environments. Preferably, this detection is invariant to a number of transformations, namely

- rotation,
- occlusion,
- scale change,
- illumination change and
- image noise,
- image flow.

A visual feature is referred to as "good" if it separates the core of information from the clutter. This basically depends on the application at hand and on the context it is used in (Jepson & Richards, 1993). For our research on vision systems for mobile robots, we define a good feature to be both independent of the transformations above and distinctively repeatable in dynamic environments.

Most features applied in literature are commonly classified either as being global, local or regional. Concerning our definition of a good feature, common global features that describe general properties of an entire image scene are rather inappropriate for our task of robot scene interpretation. While single objects can be generalized easily by simple global features, e.g. size, colour or texture attributes, finding stable and repeatable features is more complex for conglomerate scenes. However, such global features give very compact representations of significant image properties. Therefore, global features are mainly used in image-based applications like image retrieval or image annotation.

Many higher-level tasks like scene exploration or object classification and object tracking in complex scenes are grounded on local features. Being related to human visual perception, local visual features give clues for efficient scene exploration. They allow to focus on well-located interest points. Therefore, a variety of local features have been applied in a range of vision tasks, aiming at high robustness and repeatability. The Scale-Invariant Feature Transform (SIFT) proposed by Lowe (Lowe, 2004) and the Harris-Laplacian by Mikolajczyk and Schmid (Mikolajczyk & Schmid, 2002) are two popular methods of local feature detection. While the SIFT uses local extrema of Difference-of-Gaussian (DoG) filters in scale-space to produce scale-invariant features, the Harris-Laplace operator joins rotational invariant Harris features (Harris & Stephens, 1988) and Laplacian scale-space analysis into an affine invariant interest point detector. As the exploration of invariant features is an active field of research, well elaborated comparisons of various feature detectors and descriptors under a set of common transformations have been published by Schmid et al. (Schmid et al., 2000) and Mikolajczyk and Schmid (Mikolajczyk & Schmid, 2004; Mikolajczyk & Schmid, 2005).

Due to the different characteristics of local and global features, it is beneficial for some applications to combine both approaches. Lisin et al. (Lisin et al., 2005) show two methods where combining local and global features improve the accuracy of a classification task. More than another hybrid-like approach has been found in the detection of regional features, in which regions are defined as arbitrary subsets of the image. The extraction of Maximally Stable Extremal Regions (MSERs) by Matas et al. (Matas et al., 2004) highlights the advantage of a region-based approach: it produces both sparse and robust features that are particularly covariant to viewpoint change and affine transformations. Mikolajczyk et al. compare and evaluate a set of recent affine region detectors in (Mikolajczyk et al., 2005).

Regional features combine the merits of focus point localisation from local features with image-describing methods of global features. As symmetry is a regional feature, it supports the idea of regional features, especially in the context of range-based symmetry description. We reference and compare the regional symmetry features to known state-of-the-art affine region detectors. Therefore, we refer to Harris-affine regions, Hessian-affine regions, intensity-based regions (IBR), entropy-based regions and Maximally Stable Extremal Regions (MSER) that are summarized in (Mikolajczyk & Schmid, 2005). According to those recent state-of-the-art detectors, the symmetry descriptions at hand shall be included in a robust and stable regional feature detector in this section.

A time-line overview on selected work on local, regional and global features, as also on feature evaluation, is presented in Table 2:

Approach key	Global feature	Local feature	Regional feature	Evaluation	Notes
Harris & Stephens		●			Rotational invariance
Shi & Tomasi (1994)		●			KLT feature tracking
Schmid et al. (1998)		○		●	Evaluation of local detectors (Harris, Improved Harris, Heitger, Horaud, Cottier,Förster)
Milanese et al. (1999)	●				Fourier-Mellin Transform
Lowe (1999)		●			SIFT (DoG) detector
Tuytelaars & van Gool (1999)			●		Edge-based regions (EBR)
Dufournaud et al. (2003)		●			Scale invariance
Tuytelaars & van Gool (2000)			●		Intensity-based regions (IBR)
Mikolajczyk & Schmid (2002)		○	●	○	Harris-affine detector (Harris-affine, Harris-Laplace, Harris-affine regions)
Lowe (2004)		●			Optimized SIFT detector
Matas et al. (2004)			●		MSER detector
Kadir et al. (2004)			●	○	Salient-region detector
Mikolajczyk & Schmid (2004)		○		●	Evaluation of local detectors (Harris, Harris-Laplace, Harris-affine, Harris-affine region, SIFT, Laplace, Hessian, Gradient)
Yavlinsky et al. (2005)	●				Global feature densities
Lisin et al. (2005)	●	●			Combination of global & local
Mikolajczyk & Schmid (2005)		○		●	Evaluation of local descriptors (Div., GLOH, SIFT, PCA-SIFT)
Mikolajczyk et al. (2005)			○	●	Evaluation of regional detectors (Harris-affine, Hessian-affine, EBR, IBR, Salient regions, MSER)

Table 2. Selected approaches on image feature detection, description and evaluation

4.1 Symmetry Feature Description

To extract symmetry features from an image, we first use a small qualitative 1-dimensional operator from section 3.4 to acquire fast symmetry information for each image point. Horizontal and vertical symmetry axis points are detected by a line-independent maxima investigation on the symmetry data. As the pixel-based conjunction of the two resulting binary images can effect loss of feature points in cases where skewed symmetry axes indeed intersect, but do not share a pixel in the horizontal and the vertical binary image, we integrate axis points into straight line segments. Additionally, the segment representation includes useful information about each axis, e.g. length, orientation and variance. Segments with a large maximum variance correspond to curve segments. We iteratively split these at the point of maximum variance until they form straight sub-segments. The feature points are now extracted as intersections of vertical and horizontal symmetry segments. Calculating range-based DPS symmetry measures $s_{v/h}$ at each intersection of a horizontal and a vertical segment reveals an elliptical region feature $\mathbf{f}_i = (\mathbf{y}_i, \theta_i, a_i, b_i)$ parametrized by

$$
\begin{aligned}
\mathbf{y}_i &= (\, x(\mathbf{y}_i),\, y(\mathbf{y}_i)\,) & &\text{(center point)} \\
\theta_i &= (\, \theta^v + \theta^h\,) \,/\, 2 - \pi/\,4, & &\text{(orientation)} \\
a_i &= s'_v(\mathbf{y}_i), & &\text{(1st semi axis)} \\
b_i &= s'_h(\mathbf{y}_i), & &\text{(2nd semi axis)}
\end{aligned}
\tag{3}
$$

where θ^v and θ^h correspond to the orientations of intersecting segments. See Figure 5 for an exemplifying illustration of the main processing steps. Caused by line segmentation, intersections might miss the ideal symmetry maxima point, thus $s'_v(\mathbf{y}_i)$ and $s'_h(\mathbf{y}_i)$ are computed by finding the maximum vertical $s_v(\mathbf{x})$ and horizontal $s_h(\mathbf{x})$ in a small neighbourhood of $\mathbf{y}_i$. As a representation similar to the quadratic equation of central conics, each feature ellipse can also be formulated as

$$
F_i = \{\, (x,y) \in \mathbf{R}^2 \mid A_i D_i\, (x-x(\mathbf{y}_i))^2 + 2\, B_i D_i\, (x-x(\mathbf{y}_i))(y-y(\mathbf{y}_i)) + C_i D_i\, (y-y(\mathbf{y}_i))^2 = 1 \,\}
\tag{4}
$$

where
$$
\begin{aligned}
A_i &= a_i^2 \sin^2(\theta_i) + b_i^2 \cos^2(\theta_i), \\
B_i &= (a_i^2 - b_i^2)\, \cos(\theta_i)\, \sin(\theta_i), \\
C_i &= a_i^2 \cos^2(\theta_i) + b_i^2 \sin^2(\theta_i) \\
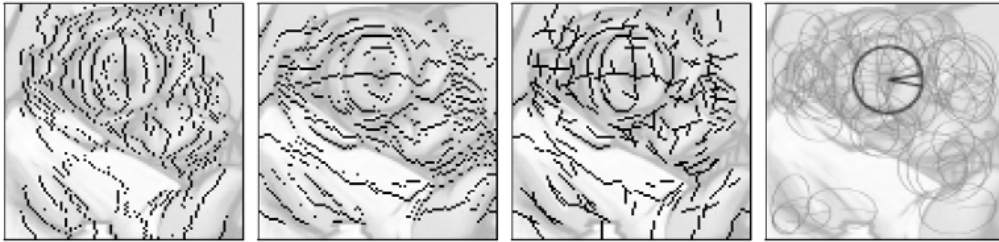D_i &= (a_i b_i)^{-2}
\end{aligned}
$$

Figure 5. From the left: Vertical and horizontal qualitative symmetry axis points, symmetry segment selection and final regional symmetric features built with range-based symmetry

4.2 Symmetry

For a part of our experiments, we use SIFT descriptor and matching (Lowe, 2004). As another model, we introduced a distribution-based colour descriptor as a very simple form

of feature description, as uncertainty of the detector in orientation can better be addressed by the generalization ability of a colour histogram. We adopt the representation of a mean-shift target candidate for robust real-time model tracking from (Comaniciu et al., 2000). The mean-shift model is robust to partial occlusions, clutter, rotation in depth and changes in camera position. The model is weighted according to the shape of the feature ellipse. Let the discrete density $\mathbf{p'}(f_i) = \{\ \mathbf{p'}_u(f_i)\ \}_{u=1..m}$ of a target candidate frame G_i describe the m-bin colour histogram descriptor of a feature $\mathbf{f_i}$. Adopted from (21) in (Comaniciu et al., 2000), this is

$$\mathbf{p'}_u(\mathbf{f_i}) = c_i \cdot \sum_{x \in Gi}\ K_i(\mathbf{y_i}, \mathbf{x})\ \delta_{uv(\mathbf{x})}, \tag{5}$$

with the kernel function $K_i(\mathbf{y_i}, \mathbf{x})$ describing a weighting over locations $\mathbf{x}$ with regard to the kernel centre $\mathbf{y_i}$. The Kronecker-δ-function compares the bins u and $v(\mathbf{x})$ for equality, where $v(\mathbf{x}) \in \{1..m\}$ maps the colour feature of location $\mathbf{x}$ to its corresponding histogram bin. Finally, c_i is a normalization constant ensuring that all $\mathbf{p'}_u(f_i)$ sum up to 1. We now derive an elliptical target frame G_i and a Gaussian kernel function K_i for each detected image feature $\mathbf{y_i}$ directly from its elliptic feature representation (4). The frame G_i enclosing each $\mathbf{x}$ in F_i can easily be defined by widening the representation to

$$G_i = \{\ \mathbf{x}\ |\ A_iD_i\ (x(\mathbf{x})-x(\mathbf{y_i}))^2 + 2\ B_iD_i\ (x(\mathbf{x})-x(\mathbf{y_i})) \cdot (y(\mathbf{x})-y(\mathbf{y_i})) + C_iD_i\ (y(\mathbf{x})-y(\mathbf{y_i}))^2 \leq 1\ \}. \tag{6}$$

Introducing the 2-dimensional Gaussian kernel function $K_i(\mathbf{y_i}, \mathbf{x})$, the correlation matrix M_i that fits the elliptical feature shape in orientation and ratio of the semi axes is given by

$$M_i = l^2\ /\ 2 \begin{bmatrix} C_i & -B_i \\ -B_i & A_i \end{bmatrix}, \tag{7}$$

where l can be used for scaling both standard deviations of the Gaussian function. Figure 6 shows two kernel shapes of l = 0.5 and l = 1.0 for an exemplary feature $\mathbf{y_i}$.
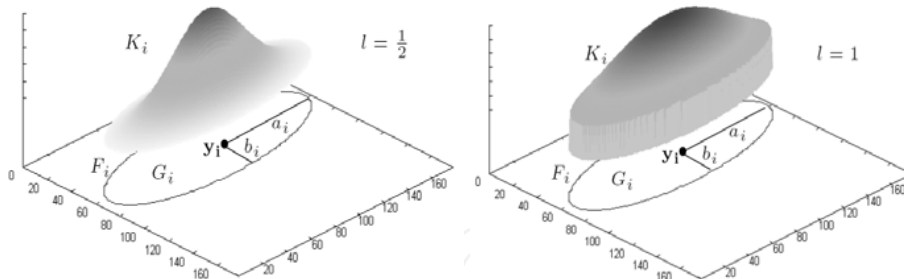

Figure 6. Gaussian distributed kernel functions for an exemplary elliptical region feature $\mathbf{y_i}$ with l = 1.0 (left) and l = 0.5 (right)

4.3 Symmetry Feature Matching for Mean-Shift Description

After the detection and colour histogram description of symmetry-based regions, a measure of correspondence has to be defined to map most correlated features. Each feature is mainly characterized by its descriptor vector, we therefore use the Bhattacharyya coefficient

$$\rho(\mathbf{f_i}, \mathbf{g_i}) = \sum_{u=1..m} (\ \mathbf{p'}_u(\mathbf{f_i}) \cdot \mathbf{p'}_u(\mathbf{g_j})\ )^{1/2} \tag{8}$$

to compute the similarity of two features $\mathbf{f_i}$ and $\mathbf{g_j}$. The common application of feature matching is given by comparing a feature $\mathbf{f_i}$ from one scene with a set of features $\mathbf{g} = \{\mathbf{g_k}\}_{k=1..n}$ deriving from a second scene. The best match for $\mathbf{f_i}$ is thus given by

$$\mathbf{f_i} \to \mathbf{g_i}: \quad \mathbf{g_i} = \text{argmax} \{ \mathbf{g_k} \in \mathbf{g} \} \rho(\mathbf{f_i}, \mathbf{g_k}). \tag{9}$$

Feature matching experiments usually describe correspondences between two feature sets $\mathbf{f}$ and $\mathbf{g}$. Depending on the final application, different matching strategies may be reasonable, namely non-injective and injective matching. Non-injective matching allows several $\mathbf{f_i}$ to be assigned to one $\mathbf{g_j}$. This mapping is adequate for applications like classification of multiple features into a number of classes. In applications, where features are meant to be non-ambiguous, one feature from one set should maximally be assigned to one feature of the other set. These assignments describe the symmetric subset of injective feature matches between $\mathbf{f}$ and $\mathbf{g}$. We found that the Mean-Shift descriptor is better for classification tasks between features, while the SIFT descriptor is better for distinctive matches.

4.4 Panoramic Evaluation on Single Images

In this section, we follow the experiments of affine region detectors in (Mikolajczyk et al., 2005) by evaluating the proposed symmetry feature detector in relation to other well-elaborated feature detectors. We compare symmetry features of a set of panoramic images to Harris-Affine and Hessian-Affine Regions (Mikolajczyk & Schmid, 2005), Intensity-Based Regions (IBRs) (Tuytelaars & van Gool, 2000) and Maximally Stable Extremal Regions (MSERs) (Matas et al., 2004). While Hessian-Affine and Harris-Affine offer edge-based regions, IBRs, MSERs and the Symmetry approach are oriented towards area-based regions. We compute these regional feature types for the 1440 × 288 panoramic image in Figure 7 (right). Results are depicted in Figure 8. The histogram in Figure 9 shows a very common distribution of image feature sizes, where the size of an elliptical region is computed as the mean value of its semi axes. Symmetry, MSER and IBR provide few and sparse features with mean feature size, while Harris-Affine and Hessian-Affine detect many small features. For our symmetry detector, the feature count and the run-time do not depend on image size only, but also on symmetric image structure. The main effort is spent on the quantitative symmetry detection, where a growing search space for each image point has to be established. We can conclude that symmetry offers the most sparse set of features with large mean feature size. Additionally, the whole process of feature description and matching is depending on feature count, so symmetry features can be described and matched fastest.

Related approaches emphasize to be covariant under affine transformations like change of scale, rotation and perspective view. Covariance terms that elliptical representations of a feature cover the same region in different images. Range-based symmetry intuitively illustrates the concept of scale robustness, as symmetry is highly proportional to scale. However, as we have only used horizontal and vertical symmetry, the detection of features is not rotational invariant. Symmetry axes of horizontal and vertical operators are able to approximate slightly skewed axes of symmetry, but are rotational invariant for rotations of $n\pi/2$ only. We found that this causes symmetry to be comparatively weak in covariance on affine transformations compared to other approaches (Huebner et al., 2006). Nevertheless, no multiple scale analysis or scale selection is needed, since scale emerges from symmetry.

Figure 7. The first and the last image of a panoramic sequence of 37 images (1440 × 288)
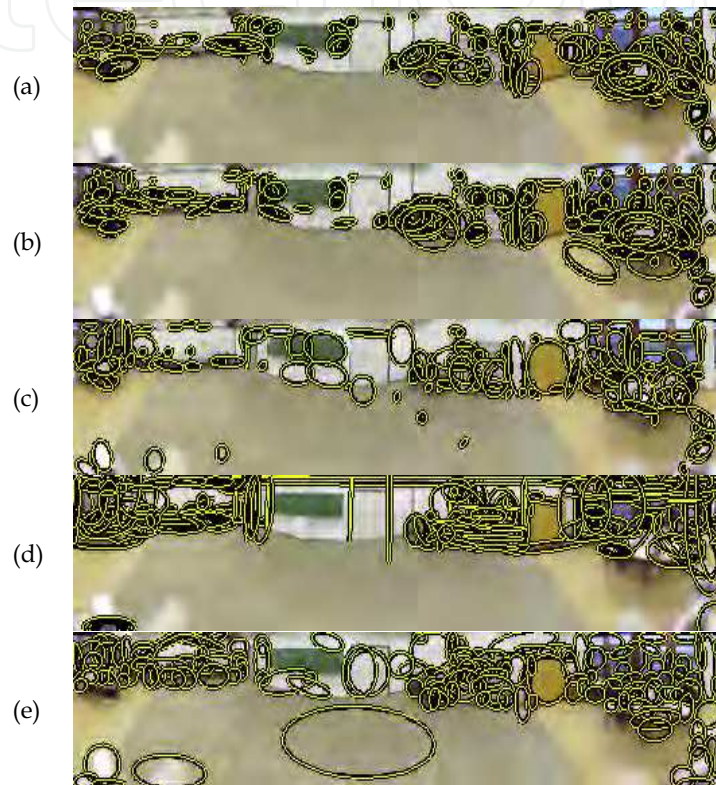
(a)

(b)

(c)

(d)

(e)

Figure 8. Regional features of the image from Figure 7 (right). (a) Harris-Affine. (b) Hessian-Affine. (c) Intensity-Based. (d) Maximally Stable Extremal Regions. (e) Symmetry Features
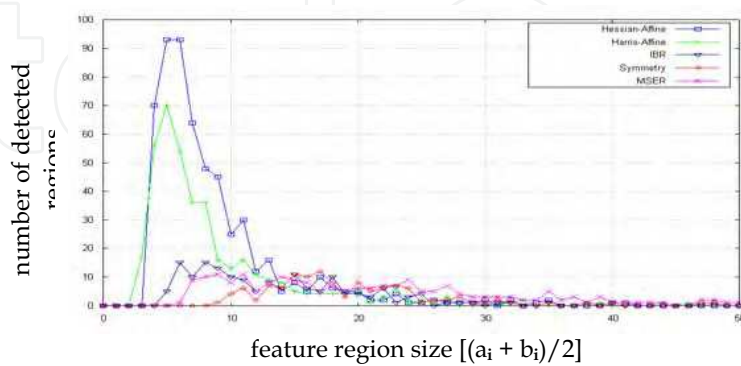

feature region size $[(a_i + b_i)/2]$

Figure 9. Histogram of feature sizes for the five regional feature detectors

4.5 Panoramic Evaluation on a Sequence of Images

In contrast to the transformations (changes in image blur, scale, rotation, perspective view and JPEG compression) discussed in (Mikolajczyk et al., 2005), panoramic warp is not an affine one. Therefore, we exploit the properties of the detectors in an evaluation experiment on panoramic warp, which naturally includes changes in blur, scale, and panoramic view, as can be seen in the panoramic samples above. We use a sequence of 37 panoramic images that was recorded during a straight movement using a mobile robot platform (see Figure 7).

For each of the five detectors, f_1 is computed, being the reference feature set of the first image. We also detect and describe the feature sets $\{ g_i \}_{i=2..37}$ with the SIFT descriptor to compute distinctive matches between f_1 and each g_i. Hereby, we evaluate how sensitive the different detectors are with regard to different levels of panoramic image warp. The number of features and feature matches are shown in Figure 10(a) and 10(b). We find again that symmetry yields very few features and matches. To rate these matches, the repeatabilities $r(f_1, g_i)$ are computed and plotted in Figure 10(c). The plot presents clearly the repeatability decrease with increasing distance for all approaches, as images differ more from the reference image along the sequence. Additionally, it shows that the matching rates of MSERs and Symmetry are best to find correspondences from the detected features.

However, detected matches are not always correct. There may be false positives, when image regions look the same. To distinguish between false and correct matches, information about the exact image transformation is necessary. In (Mikolajczyk et al., 2005), simple 3×3 homography matrices are used to define the ground truth of where a feature has to be after an affine transformation. On the one hand, panoramic image flow for robot applications is not an affine transformation. There are image regions that do not change (e.g. fixed robot parts in the image, regions along the axis of movement and regions that are far away) or others that warp in a non-linear manner according to their size and their distance to the robot. On the other hand, the environment around the robot is unknown and dynamically changing, which makes panoramic homographies for robot applications impossible to establish. Therefore, we try to approximate each homography $H(1,i)$ between image 1 and image i by a column-based histogram of feature shifts. For each match that results from the feature matchings between f_1 and g_i, we assign its radial shift in x-direction to the column. If there are more shifts assigned to one column, the mean value is assigned. Note that the results of all feature detectors are used to establish these homographies. Empty histogram cells are subsequently filled in by interpolation. To handle outliers, each fifth entry of the histogram is used as a sampling point for a cubic spline that now describes $H(1,i)$. Some resulting homographies $\{H(1,i)\}_{i=2..6}$ are presented in Figure 10(d). The graphs show increasing shift altitude and zero-crossings at the image edges 0 and 2π, respectively, as also at the image centre π. This gives obvious reason that the robot has moved away from a point in the image centre. This is correct, as the robot moved a straight path between image 1 to image 37 (see Figure 7).

After these two steps, we can compare the shifts of the feature matches to the corresponding homography for each image match. Figure 10(e) presents the comparison between the matches of the different detectors and H(1,3). For the cause that homographies are acquired by the complete feature set, they are visibly influenced by these, but outliers are clearly recognizable. The largest outlier in the example in Figure 10(e) can be detected at the left side of the image as a sample of the IBR method. Reviewing the image sequence, we find that this feature is one of those describing one of the monitor screens. It has been matched to

one of the other screens in the image and truly is incorrect. In this homography H(1,3) there are few eye-catching outliers for IBR, Harris-Affine, MSER, Symmetry and Hessian-Affine.
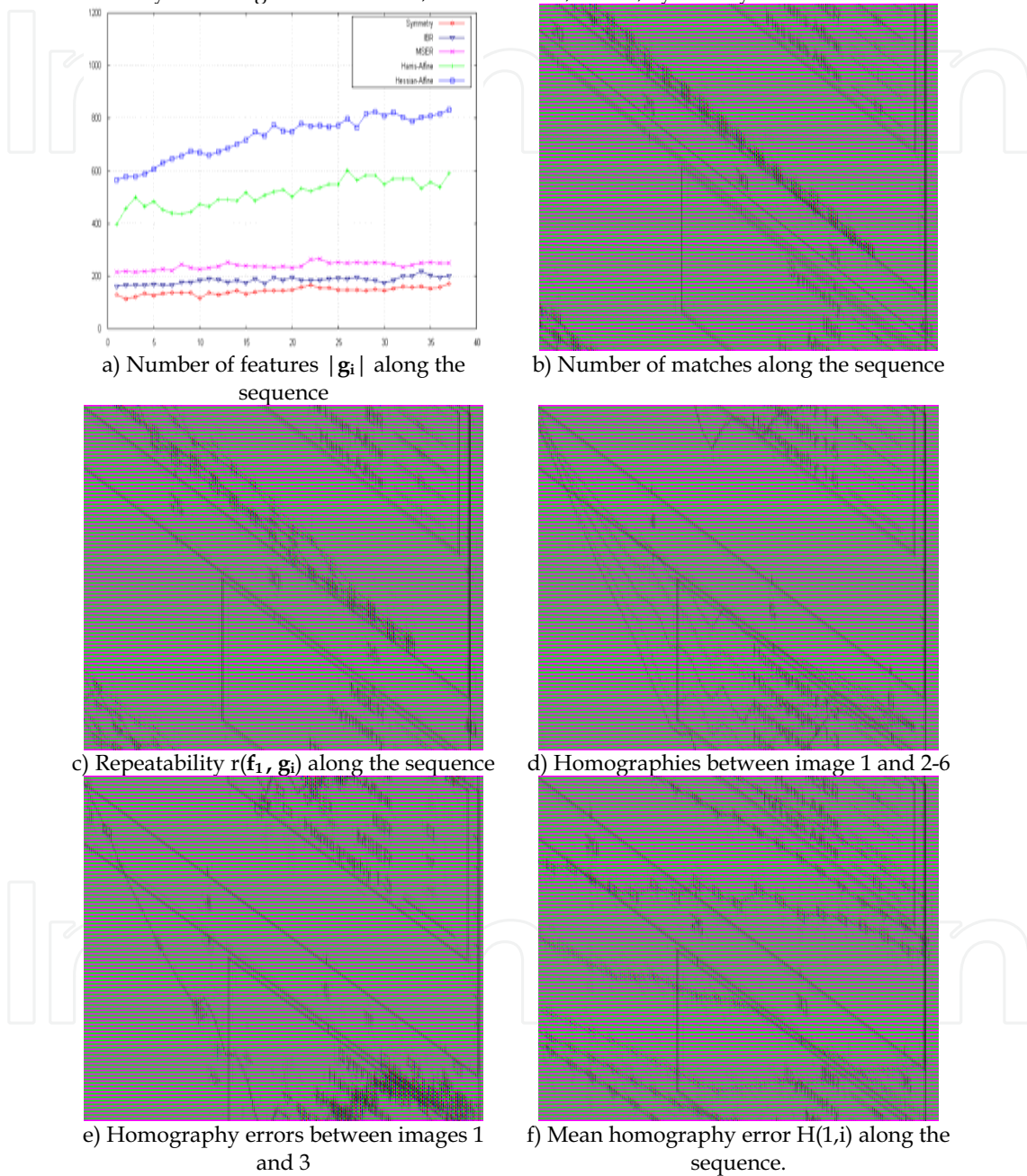

a) Number of features $|\mathbf{g_i}|$ along the sequence

b) Number of matches along the sequence

c) Repeatability $r(\mathbf{f_1}, \mathbf{g_i})$ along the sequence

d) Homographies between image 1 and 2-6

e) Homography errors between images 1 and 3

f) Mean homography error H(1,i) along the sequence.

Figure 10. For the comparison of all detectors, features of image 1 are matched to those of images 2-37 of the sequence

The mean deviation of matches about the homographies along the whole sequence is depicted in 10(f). It can be seen that matching correctness decreases for each method the more the image i differs from the reference image 1, but IBR and Symmetry provide best matching correctness for the analysed image sequence.

Concluding, the experiments show that regional symmetry features are successfully applicable for feature detection and matching during panoramic warp. No multiple scale analysis or scale selection is needed, as scale emerges directly from the range-based symmetry component of the detector. The detector offers comparatively few and significant features that support fast description and matching. Matched features are highly stable, distinctive and correct in combination with the SIFT descriptor. Another advantage of the symmetry approach is the strong relationship of extracted features to objects in the scene. Walls, doors, monitors and cabinets are frequently included by one feature.

5. Integration and Application

As we are now able to describe symmetry and apply these descriptions in terms of a regional feature descriptor, we exemplary integrate our method to a robot application based on panoramic vision. In the following application on egomotion classification, we use the Hamburg mobile service robot TASeR (see Figure 13). For further applications based on the symmetry feature approach, we reference to some of our other work on motion detection (Huebner et al., 2005) or object classification (Huebner & Zhang, 2006).

5.1 Egomotion Classification Algorithm

The homographies discussed in the previous section showed that repeatability values strongly decreases yet after few images. Figure 10(c) depicts that repeatability is less than 20% after 15 images (150cm). Thus, a precise and general estimation of depth information is hardly realizable. Another problem is that a feature offset of 0 degree between two images can have multiple causes. Either the featured object lies along the direction of movement, or it is too far so the offset is smaller than a pixel, or it belongs to the robot itself. Because of these difficulties, we do not focus on distance or egomotion estimation. However, the optical flow of feature matchings between images allows reasoning about the robot's movement. By the feature matching technique, extracts of the image flow are detectable in terms of the yet discussed partial homographies. Our goal here is to distinguish between four basic robot movements: no move, move in direction α, turn left and turn right. Figure 11 shows the theoretical image flow and homography graph classes for these movements. The amplitude of a graph is not only dependent on the distance between the two robot positions, but also on the distance to the features, thus we only check for each x the sum of signs of the feature shifts Δx on the image halves that are defined by x:

$$d_1(x) = \sum_{i=0..w/2} \delta(x+i) \,, \; d_2(x) = \sum_{i=w/2..w} \delta(x+i) \tag{10}$$

with ($\delta(j) = 1$, if $\Delta x(j) > \varepsilon$),   ($\delta(j) = -1$, if $\Delta x(j) < -\varepsilon$),   ($\delta(j) = 0$, otherwise).

The difference $d(x)$ between $d_1(x)$ and $d_2(x)$ is maximal for the x in moving direction, if $d(x)$ is larger than a small threshold t_1, so that movement direction α can be calculated as

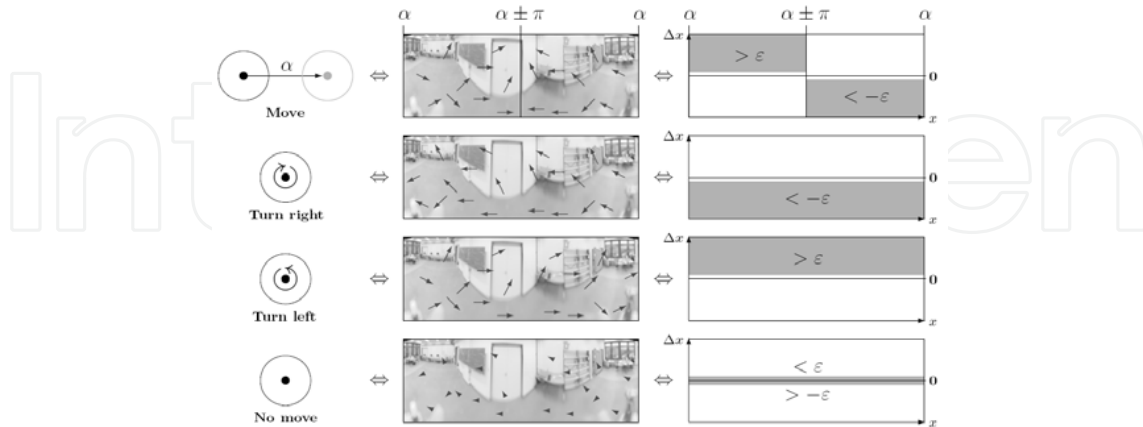$$\alpha = \text{argmax}\{x\} \, d(x) \;\; \text{with} \; d(x) = (\, d_1(x) - d_2(x) \,). \tag{11}$$

Figure 11. The four basic movements "Move α", "Turn right", "Turn left", and "No move". Typical feature shifts for those movements are shown in the centre column. On the right column, the corresponding homography sectors are depicted, e.g. a "Turn right" action is to result in feature shifts in negative x-direction only

Additionally, the product $d_1(x) \cdot d_2(x)$ is useful, as it may distinguish a sinus-shaped homography graph from a constant one. Therefore, we establish two measures c_1 and c_2 as

$$c_1 = (d_1(x) \cdot d_2(x)) \,/\, w, \quad c_2 = -c_1, \text{ if } d_1(x) < 0, \text{ or } c_2 = c_1, \text{ otherwise.} \tag{12}$$

For $c_1 < 0$, we can assume a movement of the robot in direction α. For $c_1 > 0$, a turn action or no movement is probable. To distinguish between these two, we use a second threshold t_2. c_2 finally helps distinguishing between "Turn left" and "Turn right" actions.
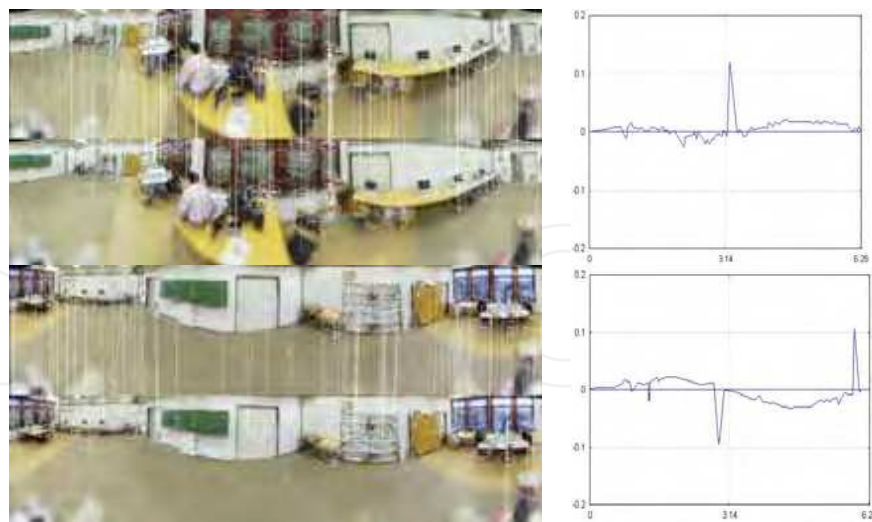

Figure 12. Top: Between images 122 and 123. The algorithm computes $d(\alpha) = -215$, $c_1(\alpha) = c_2(\alpha) = 0$ and correctly returns "No move". Bottom: Between images 24 and 25. The algorithm computes $d(\alpha) = -428$, $c_1(\alpha) = -95$, $c_2(\alpha) = 95$ and returns "Move in direction 340°"

The resulting algorithm is applied to a sequence of 200 images that were recorded by the TASeR robot. The odometry sensors allow for a final comparison of the real movements to the estimated ones. For each neighbouring image pair, symmetric regional features are computed and described by the SIFT descriptor for distinctive matching. The symmetry homography is computed like described in section 4.5 and classified by the algorithm.

From this sequence, we show two examples for "No move" and "Move left" in Figure 12. As can be seen from the matching, the homography graphs and the measures d, c_1 and c_2, the algorithm also offers robust results for homography graphs that are influenced by failure matches. The same robustness is also shown by the results on the whole image sequence, as presented in Figure 13. Comparing the real robot route with the estimation, we find a very high correctness of movement classification. Although correctly classified, there is uncertainty in the estimation of the movement direction samples α, which ideally should all be 0.
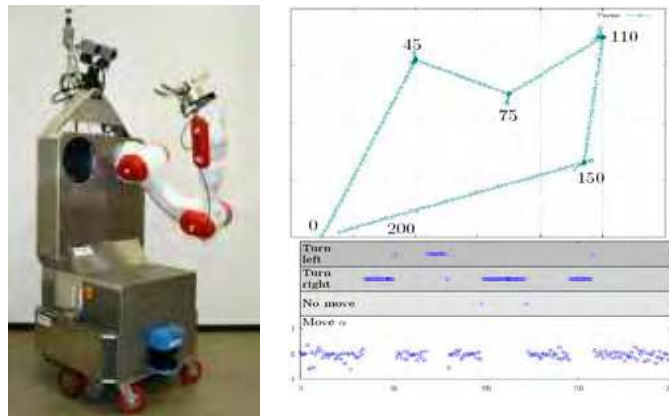

Figure 13. Left: The TASeR robot. Right: The experimental route map delivered from the odometry (top) and the movement classification with our simple algorithm (bottom).

6. Conclusion

In this work, bilateral symmetry has been proposed as a concept for the extraction of features from the visual data and their application to robot navigation tasks. Symmetry in shape and vision is strongly motivated by biological and psychophysical aspects. It is a natural feature that can be found in many scenes, whether they show structured indoor or unstructured outdoor environments. We conclude with a review on the three main topics:

1. Symmetry as a Feature: Symmetry has been investigated in several domains like biology, psychophysics, architecture and art. Accordingly, symmetry has also been applied as a valuable attentional feature for the extraction of regions of interest or for object description by symmetric properties in computer vision.

Motivated by psychophysical experiments on symmetry perception, a fast and compact one-dimensional operator was supposed earlier (Huebner, 2003) to handle horizontal and vertical bilateral symmetry measures only. The operator overcomes the problem of symmetry detection methods in literature that use large operators which are mostly unsuitable for robotic real-time tasks. However, each of these strength-based operators returns a relative, commonly normalized value of symmetry for each image element. For

this purpose, a novel method to generate robust range-based symmetry values was proposed that produces symmetry range information for each image point (Huebner et al., 2005). This approach is based on an algorithm computing bilateral quantitative symmetry information using an adopted Dynamic Programming technique. Qualitative and quantitative symmetry measures offer a variety of symmetry representations - especially those of symmetry axes - for higher-level image processing tasks.

It was shown how globally and versatile symmetry can be used as a feature. Even beyond the context of image processing and visual data, symmetry can be used as a general feature of structure. A further task in this topic would be the further workout of the quantitative symmetry approach. The calculation of the Dynamic Programming Symmetry search spaces might be optimized and thereby accelerate computing time. Another open issue is the use of search space path structure for quantitative symmetry computation.

2. Regional Symmetry Features: In this part, a new regional symmetry feature matching approach was proposed. It comprises several modular techniques for detection, description and matching of image features based on the symmetry types developed in the previous section. While the qualitative symmetry operator describes symmetry as a relative degree and the quantitative operator describes symmetry as a range, advantages of both were combined in a stable regional feature detector. In combination with descriptors, symmetry features can robustly be matched. The descriptors used were the famous gradient-based SIFT and a Mean-Shift approach that was adopted to the task of feature description. The evaluation including state-of-the-art regional feature detectors shows that the symmetry feature approach is well applicable for robust feature recognition, especially for panoramic image warp. Description and matching of symmetry features is very robust and faster than other approaches that derive larger feature sets. Additionally, symmetry features are strongly related to objects in the scene. Walls, doors, monitors and cabinets are frequently included by one feature.

Besides the advantages of regional symmetry features, their sensibility to rotation is due to this works concentration on horizontal and vertical symmetry measures mainly. This invariance would be an important step to support the task-spanning robustness of the approach. The measures of covariance and overlap might benefit from an additional rotation invariance of the proposed features. Therefore, a further task is to efficiently find a robust orientation measure of symmetry and symmetric features. Along and perpendicular to this orientation, the proposed twofold quantitative symmetry measures could be used.

3. Integration and Application: The third topic addressed the applicability of the developed symmetry features for robot navigation by panoramic vision. For this purpose, the mobile service robot TASeR from the Working Group Technical Aspects of Multimodal Systems at the University of Hamburg was used. The capability of symmetry feature matching with regard to simple classification of robot egomotion was presented. The integration of the developed visual symmetry features into high-level object recognition and robot navigation tasks in dynamic environments is thereby motivated.

It is important to state that the step from one or more features to an object has not been made in this work. Features are natural low-level points or regions of attention that are supposed to describe significant visual information and thus might be interesting to be analysed. Objects are understood as higher-level entities filled with semantic descriptions. Those are embedded in higher-level applications like object recognition or autonomous robot navigation of intelligent systems. These tasks are theirselves wide areas of research

such as the detection of robust and natural image features that has been treated in our work. As presented in this work, symmetry can support these tasks.

Returning to the image of a construction set that has been used in the introduction, symmetry is just one of the construction blocks that might help intelligent systems to perceive and act in dynamic environments.

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Vision Systems: Applications

Edited by Goro Obinata and Ashish Dutta

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