

A DUALISTIC VIEW OF MOTION AND INVARIANT SHAPE ANALYSIS

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A systematic procedure for the extraction of multiple-invariant shape descriptors is introduced which is based on generalized auto-correlation functions. It can be carried out in the same parallel processing network which serves for the extraction of motion parameters via flow-field analysis. It is argued that this dualistic processing principle is neurobiologically relevant. Models of neural networks are presented and their properties are discussed for both modes.

1. INTRODUCTION

The generation of invariant shape descriptors and the characterization of object- or ego-motions are essential for the successful behaviour of creatures who are living in a natural environment. On the other hand, both visual performances are of increasing importance in the field of robotics. In this article it is argued that a certain part of the visual system is suited to jointly perform both tasks, depending on the stimulus: moving or non-moving. The question arises, whether this putative biological solution – which may have evolved due to the demand for self-organization of neural computing structures – is of great value for the construction of technical systems that shall serve for the mentioned purposes.

Differing from the underlying research work which was aimed to explain multiple-invariant pattern recognition in the visual system the following article starts with the explanation of the basic device which enables a neural network to perform both tasks: invariant shape description and object-independent motion analysis. After this unit is introduced the mathematical principles of both methods of parameter extraction are presented, as well as exemplified by two types of motion analyzing circuits and by their corresponding similarity-invariant shape descriptors.

2. ELEMENTARY MOTION DETECTOR

A variety of mechanisms for the detection and analysis of motion are already proposed in literature (cf. the survey given by Ruff et al. in [1]). All of them have their roots in the model circuit developed for the insect eye by Hassenstein and Reichardt [2,3]. Under the following assumptions, however, it is sufficient to consider a simplified version of the original circuit:

- The detector unit acts on a preprocessed image representation displaying line-like pattern versions (contour or skeletoned versions).
- The detector unit works uni-directionally.
- The detector unit is velocity selective, that is, velocity is not coded into the amplitude of the output signal of each unit but different units are tuned to different velocities.

2.1 Dynamic Properties

Any elementary motion detector unit must perform at least a second order operation in space and time. More precisely, the temporal succession of signals at two points in the pattern representation must be compared (correlation). Figure 1a shows a simplified Hassenstein/Reichardt-detector (HRD) – by which this task can be performed under the above mentioned conditions – together with

a symbolized stimulus. This unit has a tuning velocity

$$v_{\text{tun}} = \Delta x / \Delta T \quad (1)$$

for points moving in the positive v -direction, that is, for v_{tun} the comparator 'o' delivers an output signal. Thus, for a multiplying comparator, the output signal is the squared signal amplitude at the considered pattern points (auto-correlation). For exotic stimuli, such as periodic patterns (e.g. gratings) that are linearly moving in a fronto-parallel plane, this HRD signals multiples of the real pattern velocity as well. However, such stimuli rarely appear in natural environments and the mean output signal of sets of equally tuned and spatially distributed HRDs is commonly considered for motion analysis thereby reflecting quite well the true velocities of real world stimuli.

In the following it is assumed that v_{tun} is determined by the spacing Δx of the points from which the input signals of a unit are taken. This kind of tuning is in accordance with the findings of van de Grind et al. [4] who showed psychophysically for humans that, for common velocities ($>2^\circ/\text{s}$), the delay ΔT is constant (typically: $\Delta T_{\text{hum}} \approx 60\text{ms}$). Thus, one can suspect interneurons to be responsible for the delay. (According to the investigations of Koch and Poggio [5] the coincidence interval δT of a neural comparator can be assumed to be about 1% of ΔT .)

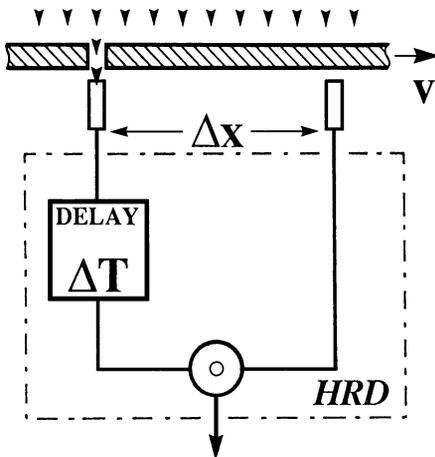


FIGURE 1a

Velocity selective and uni-directionally working motion detector unit that requiring line-like input patterns

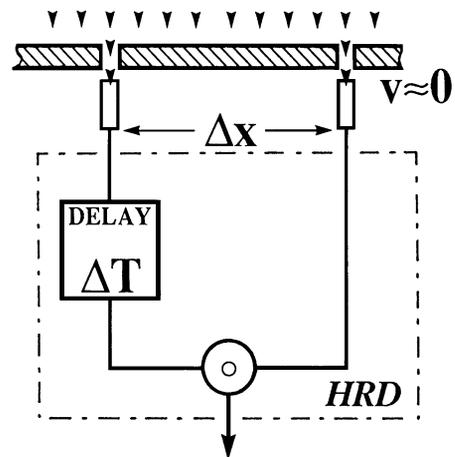


FIGURE 1b

Motion detector unit in the static mode ($t > \Delta T$) signals to which extent a dipole relation is present in a pattern

2.2 Static Properties

Besides these dynamic properties (spatio-temporal correlation) the considered HRD units perform pure spatial comparisons within static patterns ($t > \Delta T$). This spatial auto-correlation mode is symbolized by Figure 1b. It will be demonstrated later in this article that parts of the so-called *generalized auto-correlation function* (ACF) of order two can be computed from pictorial patterns via the so-called *dipole approach*, if

- many HRD units are suitably arranged in the plane of the pattern representation,
- their output signals are appropriately combined, and
- the distribution and range of spacings Δx are adapted.

This *generalized auto-correlation analysis* is the basis for a systematic approach to invariant shape descriptions of pictorial patterns.

There is no direct active switching between the dynamic and static mode of analysis (dualism) – except by changes in observer-induced motion (e.g., eye movements and/or body motions): transients occur if the relative motion between an object and the retina exceeds or falls below the velocity v_{min} defined by ΔT and the spatial resolution Δx_{min} of the considered pattern representation.

3. GENERALIZED AUTO-CORRELATION FUNCTION

The generalized ACF of order m , $c(\mathbf{z}_1 \dots \mathbf{z}_m)$ of a pattern function $b(\mathbf{x}) \geq 0$ is mathematically defined [6,7,8] by

$$c(\mathbf{z}_1 \dots \mathbf{z}_m) = \int \bigwedge_{i=1}^m [b(\mathcal{T}_i\{\mathbf{x}\})] d\mathbf{x} \quad \text{with } \mathbf{x} = (x,y)^T \quad (2)$$

where $\bigwedge_{i=1}^m [\dots]$ symbolizes an arithmetic operation of the conjunctive type on m terms (order m), e.g., multiplication;

and $\mathcal{T}_i = \mathcal{T}(\mathbf{z}_i)$ indicates geometric transformation rules (mappings $\mathbf{x} \rightarrow \mathbf{x}'$) acting on the argument \mathbf{x} of the pattern function and which are characterized by the v -dimensional vector $\mathbf{z} = (z_{i1} \dots z_{iv})^T$.

For nearly all cases (\mathcal{T}^{-1} must exist) the generalized ACF of order two can thus be written

$$c(\mathbf{z}) = \int b(\mathbf{x}) \circ b(\mathcal{T}\{\mathbf{x}\}) d\mathbf{x} \quad (3)$$

where ' \circ ' denotes a comparison operation of the conjunctive type. Equation (3) defines a rule for the extraction of the invariants of a pattern under defined transformations. More precisely, the degree is specified to which invariant properties are present in a pattern: the pattern is transformed and for every value of the transformation parameter the distance to the untransformed original is determined according to a suitable measure. Generalized ACFs that depend merely on one type ($v=1$) of geometrical transformation \mathcal{T} , by definition are invariant under this very type of transformation, independent of its extent (inherent invariance). In general this does not hold for several types of applied transformations and/or for invariance under several types of transformations. In such cases the desired multiple-invariant intersection of the sets of invariants must be determined.

Two essentially different methods for the evaluation of the generalized ACF must be considered. While the approach via explicit transformations of a pattern function is straightforward, the second method, via generalized dipole moments, is less obvious. For the latter comparison results are integrated that are gained from all those two pixels (dipoles) of the pattern which are related by the same parameter vector \mathbf{z} . This implicit approach can be realized by suitably arranged HRDs that act on static patterns: each two-point relation (dipole) is represented by the output of a HRD.

4. FLOW-FIELD MOTION ANALYSIS

Ordered arrangements of HRD units that look onto the considered planar pattern representation permit the extraction of motion parameters. For this purpose the structurally stored models of (global) vector-fields (spatial arrangements of HRDs) are in some sense 'correlated' with flow-fields induced by the projection of moving objects onto the pattern representation. The resulting levels of activation of the different model circuits allow for the evaluation of the motion parameters of moving objects. In simple systems maximum detection is sufficient for this purpose. The advantages of this kind of flow-field analysis are

- the independence from the form of the moving objects,
- the tolerance with respect to noise in movements, that is, the ability to extract their dominant components, and
- the feasibility to segment compound motions according to the implemented vector-field models.

Two simple cases of flow-field processing are now introduced:

- The monocular analysis of pure depth-motions of approximately planar objects that may occur, for instance, when moving through a forest while looking straight ahead to the horizon.
- Rotatory motions in fronto-parallel planes, as they occur, for instance, by bending the head to the shoulders.

4.1 Depth-Motion

Only a few fundamental principles of projective geometry are required to understand the here proposed depth-motion analyzer. They are explained with the help of Figure 2 which shows a sectional view of an idealized pinhole-camera looking in Z-direction. The centre of projection is at the point $Z=0$, $r=0$ and, for convenience, the sensory plane (coordinate r) is situated in front of this point at the distance L . Then, the relation between the position (R,Z) of an object point in the field of view and its projection onto the sensory plane (or better: retinotopic representation) is given by

$$r = L \cdot R / Z . \quad (4)$$

Obviously, position r in the projection depends on the lateral position R of the object point with respect to the line of sight (Z -axis). Therefore, any analysis that is directly based on Equation (4) is object-dependent. Conversely, any approach to object-independent motion analysis must be based on the invariant quantity of depth-motion, namely the scale factor

$$s = Z_i / Z_{i+1} = r_{i+1} / r_i . \quad (5)$$

According to the investigations of Regan and Beverley [9] this appears also to be true for the human visual system. A HRD-based circuit for the object-invariant evaluation of these scale factors is partly sketched (factors $s=1.5$ and $s=2$) in Figure 2 beneath the r -axis. The factors s , defined between (temporally) consecutive positions of object points in their projection onto the representation are referred to the origin $r=0$, i.e., to the representation of the centre of the 'fovea'. The output signals of HRDs that code the same scale factor are summed. Each thus defined set of HRDs makes up an isotropic and radially organized network. A complete analyzer system can be estimated to consist of 50...100 of such parameter specific networks typically covering the range of scale factors from 1.01 to 4. Signals that are specific for depth-motions are derived in a second stage of analysis in which the correct temporal succession (interval again ΔT) of scale factors is tested according to the hyperbolic law expressed by Equation (5).

$$s = 1 + \Delta T / t \quad (5a)$$

The output signals of this stage can be used to determine the depth positions of objects in the case of ego-motions with $v_z = \text{const}$, or for the computation of the so-called time-to-contact.

Systems for the analysis of depth-motions having velocity components in R-direction – i.e., object-motions on straight tracks that intersect the projection of the line of sight under angles $\gamma \neq 0^\circ$ – are identical to the above described but centred extrafoveally around (fixed) points with radial coordinates

$$r = L \cdot \tan \gamma . \quad (6)$$

Such flow-fields are caused, for instance, by ego-motions if the line of sight does not coincide with the direction of movement.

4.2 Fronto-Parallel Rotation

Analyzers for front-parallel rotations are similarly structured. The systems are centred around centres of rotation (fixed points). Each system consists of isotropically organized networks with a common fixed point which are selective for different angular velocities ω . Each network is made up by concentrically arranged HRDs whose input signals are taken from points laying on the same circle and that are separated by the same angle

$$\psi = \omega \cdot \Delta T . \quad (7)$$

In order to avoid 'crosstalk' between systems with different fixed points the continuity of the activity of each system is monitored in a second stage again for an interval of ΔT .

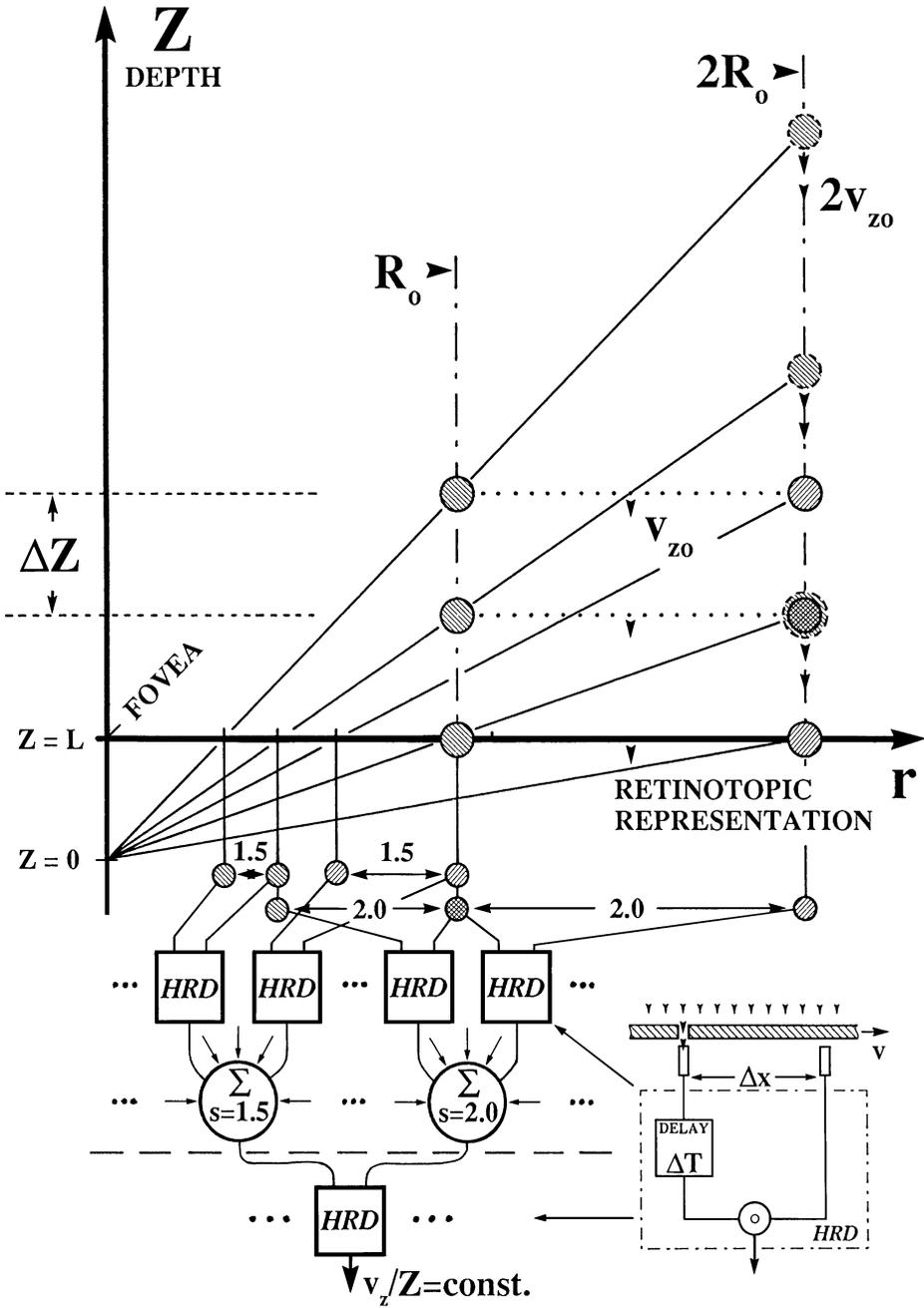


FIGURE 2

Central projection of two approaching (velocity $v_{z_0}=\text{const}$) object points (large hatched discs in solid circles) – drawn for two successive intervals $\Delta T=\Delta Z/v_{z_0}$ – onto a planar retinotopic representation (projection plane $Z=L$). Beneath the r -axis: partial view of a two-stage and HRD-based network for the object-independent extraction of depth-motion parameters using flow-field analysis.

5. INVARIANT SHAPE DESCRIPTORS FROM FLOW-FIELD ANALYZERS

In this section the extraction of two shape descriptor functions is exemplified which are invariant under all similarity transformations, i.e., rigid translations, scale changes, rotations and reflections (similarity-invariance). It is shown that the introduced flow-field analyzers for depth-motions and fronto-parallel rotations represent appropriate structures for the evaluation of these multi-invariant features.

Figure 3 represents a top-view onto a part of the first stage of a more realistic model structure for depth-motion analysis. The radial arrangement of areas (large circles) from which the input signals of the HRDs (small lettered circles) are collected is centred around the fixed point, e.g., the representation of the fovea. Only one network defined by $s=1.5$ is sketched. Other networks can be thought as being superimposed onto the shown one. The integration areas of the HRD units increase with eccentricity in order to keep the relative error constant. (For reasons of clearness only three interleaving spatial sequences of HRDs are drawn.) Furthermore, flow-field analysis is carried out locally within overlapping and radially subdivided segments (bold frames).

A corresponding system structure for the analysis of rotatory motions is straightforward.

5.1 Descriptor Function for Size Relations

In its static mode a complete and globally acting analyzer of the type shown in Figure 3 calculates the zoom-ACF

$$c_{s_0}(s, x_f=0, y_f=0) = \iint b(x, y) \cdot b(x/s, y/s) dx dy . \quad (8)$$

This ACF depends on scale factors of the considered range. It is restricted to scale changes referred to the origin (fixed point: $x_f=0, y_f=0$), e.g., the foveal representation. As mentioned in Section 3., this function, by definition, is invariant with respect to arbitrarily zoomed pattern versions (inherent invariance). This holds true independently of the number and the scale range of the implemented networks, that is, of the applied scale factors. However, the zoom-ACF c_{s_0} is additionally invariant under rotations around the origin and under reflections with respect to axes passing through the origin.

In order to get rid of the limitations imposed by a certain fixed point the extraction of a similarity-invariant descriptor function $C_s(s)$ is proposed.

$$C_s(s) = \max_{x_f, y_f} \{ c_s(s, x_f, y_f) \} \quad (9)$$

Equation (9) presupposes many complete systems of analyzers which are centred around different fixed points. This must also be claimed for the analysis of arbitrary depth-motions as outlined in Section 4.1. The descriptor function C_s indicates the maximum degree of size similarity of a pattern as a function of scale. Hence, patterns consisting of straight lines that join or intersect at a common point result in $C_s = \text{const.}$ Contrarily, any fraction of a circle line leads to a sudden decrease of this function for $s \neq 1$.

5.2 Descriptor Function for Angle Relations

In its static mode a complete and globally acting analyzer for fronto-parallel rotations computes the rotation-ACF

$$c_{\psi_0}(\psi, x_f=0, y_f=0) = \iint b(x, y) \cdot b[r \cdot \cos(\varphi + \psi), r \cdot \sin(\varphi + \psi)] dx dy \quad (10)$$

with $r = \sqrt{x^2 + y^2}$ and $\varphi = \arctan(y/x)$.

This ACF depends on rotation angles ψ and is restricted to rotations around the origin (fixed point: $x_f=0, y_f=0$), e.g., the foveal representation. Like the zoom-ACF the ACF c_{ψ_0} is invariant under rotations (inherent invariance) and scale changes, both with respect to the origine and under reflections with respect to axes passing through the origin.

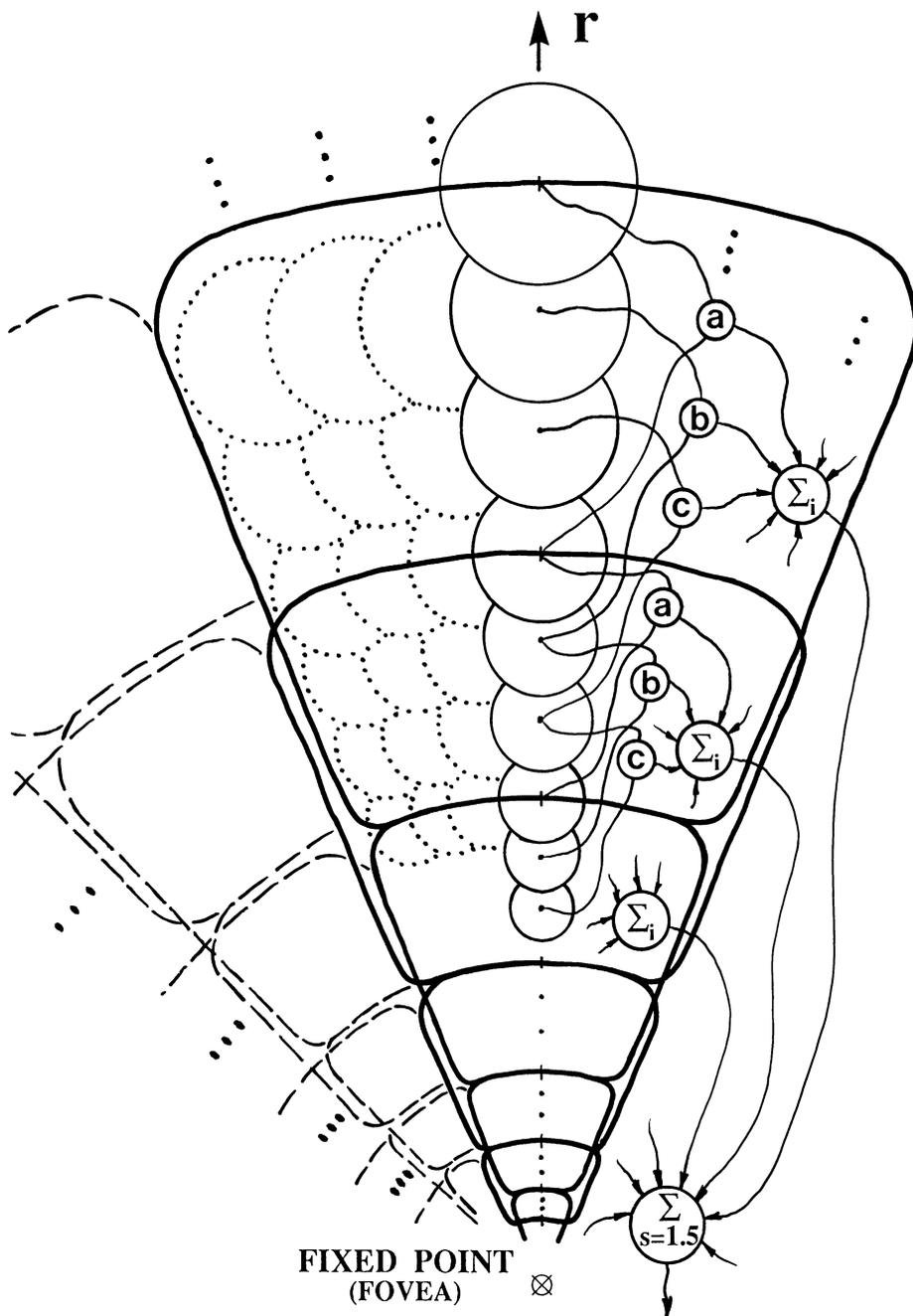


FIGURE 3

Partial top-view of a subdivided network (characterized by the scale factor $s=1.5$) serving for the analysis of depth-motions (first stage). Bold frames: overlapping local analyzing areas (receptive fields of Σ_i -neurons); small lettered circles: HRD units (nonlinear subunits) forming three radially interleaving spatial sequences; large circles: areas from which the input signals of the HRD units are collected.

Again a similarity-invariant descriptor function can be derived

$$C_{\psi}(\psi) = \max_{x_f, y_f} \{ c_{\psi}(\psi, x_f, y_f) \}, \quad (11)$$

and again systems of analyzers differing in their centres of rotation (fixed points) are required. This claim is desirable from the motion analysis point of view as well. The descriptor function C_{ψ} reveals the maximum angular bindings of a pattern. Consequently, a perfect circle is the only extended pattern function with $C_{\psi} = \text{const}$. Regular polygons or star-like patterns result in periodic functions C_{ψ} .

Further properties of the descriptor functions C_s and C_{ψ} are exemplified, together with characteristics of related descriptors, in [7] and in greater detail in [10].

5.3 Local Analysis

The extraction of motion parameters via local flow-field analysis within subdivided networks can result in estimates about the size of the moving object and its position with respect to the vanishing-line, i.e., the line passing through the projection centre and the considered fixed point. Another reason for local analyses is the limited fan-in of the summation units. If the comparison operations are performed by nonlinear interactions of neighbouring dendritic synapses [11,12,13,5] whose results (e.g., products) are summed near the soma of a neuron, then only some thousands of HRDs can contribute to every sum. Even if a coarse pattern representation is assumed, only moderately extended analyzing areas can thus be expected each containing typically less than 100×100 pixels.

For the local computation of generalized ACFs mainly two parameter-dependent conditions must be met by the structure of the networks (cf. Figure 3):

- Each local analyzing area must allow at least twice the application of the considered transformation parameter without leaving its boundaries.
- The overlap must measure at least the single application of the considered parameter.

For depth-motion systems this means a minimum radial extent of the local areas of at least s^2 and two radial sequences of them – each covering a complete segment of the pattern representation – which are shifted with respect to each other by the factor s . For the rotation analyzers a minimum circular extent of the local areas of 2ψ is required together with two circular sequences of them – each covering a complete ring of the pattern representation – which are rotated with respect to each other by the angle ψ .

5.4 Fixed Point Descriptors

Finally two other powerful shape descriptors should be mentioned. They invariantly characterize the fixed point patterns $f_s(x_{opt}, y_{opt})$ and $f_{\psi}(x_{opt}, y_{opt})$ which are given by the positions of the optimal fixed points and by their frequency of occurrence. These patterns can be determined during the evaluation of the descriptor functions C_s and C_{ψ} and both of them can replace the pattern function $b(x, y)$ in Equations (8) and (10) (hierarchical processing). The resulting features describe inner bindings of the configurations of optimal fixed points and thus express abstract pattern properties like compactness and complexity of pattern functions. These descriptors are exemplified in [10].

6. BIOLOGICAL RELEVANCE AND IMPLICATIONS OF THE DUALISTIC PROCESSING PRINCIPLE

J.J. Gibson states [14] that changes are the only way to make invariants obvious. This dialectic formulation may theoretically justify the presented dualistic approach; but there are other more pragmatic reasons, for instance the problem of system formation: self-organization (maturation) of neural networks of the type sketched in Figure 3 appears impossible from the shape analysis point of view. A system for motion analysis, however, is quite likely to be structured via ego-motions of the creature. Under this condition, the object-independent functioning of the resulting motion analyzers is a direct consequence of the crucial rôle which common properties of real world motion/movement-stimuli play for self-organization processes: only great numbers of identical stimuli (repeated temporal coincidence of input signals) lead to the consolidation of synaptic interconnections.

It was shown elsewhere [15,16] that invariant shape descriptors are vital for the survival of creatures living in a natural environment. The main advantage of the here proposed multiple-invariant descriptor functions is their high descriptive power and their property to express symmetries, congruences, similarities, etc. of patterns, i.e., categories of (human) form perception that are known from Gestalt-psychology and are outside the reach of template matching techniques, including integral transformations. It is shown in [10] that none of the yet known methods is biologically plausible to a comparable degree.

There is experimental evidence for the described processing principle, at least to a certain extent. First of all, neural systems for flow-field analysis of the discussed type were recently identified neurophysiologically in monkeys and cats by various research groups [17,18,19,20]. The dynamic properties of receptive fields of model neurons in the proposed networks agree well with those that could actually be measured (for a discussion see [10]). Although the responses of the neural motion analyzing systems to static stimuli were not really tested neurophysiologically, some of the experimental data obtained by Price et al. [20] (cf. Fig. 12c) show the expected properties which are derived and listed in [10]. Psychophysical investigations show that shape analysis of moving objects is impossible if pursuit (eye) movements are prevented [21]. By more recent experiments, reported by McLeod et al. [22], it could be demonstrated that the human visual system segregates randomly distributed displays of moving and non-moving symbols into the moving and static group and then performs parallel form analysis (Treisman's paradigm: visual search) within either group (preferably the moving one) without influence from the items of the other group. Furthermore it is known from research in the field of eye movements that the distribution of fixation-durations between successive saccades peaks around 180ms and is zero for intervals shorter than typically 80ms [23,24]. This fact indicates that a minimal time ΔT is required for shape analysis.

Motion analysis based on comparisons between flow-fields and structurally stored vector-fields allows the explanation of a variety of psychophysical findings in the field of motion perception, such as motion cooperativity, motion capture and related coherence effects, as well as motion segmentation [10]. A recently introduced purely computational (not structural) concept [25] which is similar to the here proposed, leads to comparable conclusions concerning the perception of motion.

Finally it must be mentioned that neural models of the kind shown in Figure 3 – which consist of neurons as summing devices for large numbers of nonlinearly interacting input signals at their dendrites (HRDs) – conform well with the discovery of so-called subunits which are conjectured to constitute receptive fields, at least those of the complex type [26,27]. Consequently, the spatial resolution of a neural system can no longer be estimated by considering the extension of receptive fields, and isolated HRD units are not directly accessible by common neurophysiological measuring techniques. Moreover, commonly measured receptive fields of neurons in general do not allow statements about the rôle they play for signal processing in networks.

7. CONCLUDING REMARKS

Although merely two types of processing systems are considered in detail throughout this article further systems, e.g., for the flow-field analysis of other types of three-dimensional motions of (non-planar) objects can result in affine or even projective ACFs from which the extraction of multiple-invariant shape descriptors is in general no longer as easy. However, invariance under small and local pattern deformations is always guaranteed by the space-variant averaging property of the integration areas of the HRD inputs (cf. Figure 3).

The introduced concept for the invariant description of pictorial patterns is one of few examples for models of visual information processing at the *signal level* for which a biologically plausible structure could be found: On one hand, parallel computing neural networks had to be developed which are suitable to perform the operations formulated by the Equations (8) and (10). On the other hand, explanations had to be given for the maturation of the required structures, i.e., of the highly specific interconnections between neurons of various layers. The dualistic approach exemplifies again fundamental differences between biological and technical solutions of information processing tasks.

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