A Humanoid Vision System for Interactive Robots*

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Abstract

ESCHeR: A binocular active vision platform with space variant lenses has been developed. The custom built lenses provide 120 degrees field of view with maximum 7.7 times magnification in the fovea versus periphery. Two types of vision processes have been developed on this platform; (1) Motion segmentation based on optical flow, and (2) Stereo segmentation by zero disparity filtering based on a phase disparity method. Both processes produce feature maps with pixelwise confidence values, which are then fused together using the confidence values to produce robust estimation of the segmented target position and velocity. Integrated with a high performance gaze control based on Kalman filter, the entire system runs at frame rate. The system performs the task of detection and pursuit of moving deformable objects in cluttered environments without a-priori knowledge of the target shape, color, size, or texture. This system provides the important fundamental performance for intelligent robots which interact with humans.

1 Introduction

Adaptive human interaction requires particular kinds of visual functionalities, such as monitoring human actions, learning them by imitating, helping or protecting by reacting to the observed actions, etc. As a prerequisite for those functionalities, we need a vision system which has the following set of characteristics: (1) Works in uncontrolled complex environments. (2) Deals with arbitrary and often unknown objects. (3) Deals with both large (i.e. in a room) and small (i.e. desktop) target movements. (4) Very robust. (5) Operates in real time (of course).

In this paper, we focus on the set of basic visual skills which constitute the solid and reliable foundation for the visual functionalities discussed above: the ability to detect and follow, without even understanding what it sees, human gestures such as hand and head motion.

Our system fulfills all the requirements discussed above. For example, when somebody enters the room it finds and tracks him/her while approaching the desk, when he/she starts manual actions like picking up objects from the desk, it focuses on the hand motion, and when it observes no motion for a while, it looks around for some other target. All these happen in real time, in a cluttered environment with arbitrary objects and no markers, quite robustly. Although there has been numerous work in robot vision, it is still very difficult to achieve the overall performance such as our system exhibits. It has been achieved as a result of an integrated approach including special sensor hardware, fusion of

*The vision processing part of the presented work resulted from the Ph.D. project by Sebastien Rougeaux supervised by Yasuo Kuniyoshi. The main body of the paper is based on [18].
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parallel processed visual features, and a sophisticated real time system design.

In the next sections, we will first describe our implementation of two visual cues commonly found in biological visual systems. By fusing these cues, our high performance binocular head nicknamed ESCHeR, which combines active and space-variant vision characteristics, can detect and track in real-time moving and deformable objects in cluttered scenes. We will also present our latest experiment with neural net based hand-eye coordination learning, which is another step towards adaptive interaction system.

2 ESCHeR

ESCHeR [11] (E[tl] S[tereo] C[ompact] He[ad for] R[obot vision]) is a binocular active vision system developed as an essential component for an interactive robot system. Many aspects of the system are biologically inspired, e.g. the space variant sensing, active gaze control, optical flow and zero disparity filtering.

![Figure 2: ESCHeR: a high performance stereo-head.](image)

2.1 Mechanical design

The mechanical design exhibits four degrees of freedom for eye motions: independent left and right vergence with a common tilt supported by a common pan (Fig. 2). This stereo-rig can achieve peak acceleration and velocities comparable to the human eye capabilities (Table 1). Moreover, although its mechanical performance are slightly inferior to the dynamics of binocular platforms like the latest Yorick 8-11 [5] or even TRICLOPS [25], ESCHeR exhibits a much more compact and light design (Table 2), making it suitable to be mounted on a mobile vehicle or even a robotic manipulator.

2.2 Space-variant sensors

The most distinguished parts of ESCHeR are its "foveated wide angle" lenses[12]. Our lens simulate human visual system’s compromise between the need for a wide field of view for peripheral detection and the need for high resolution for precise observation under limited number of pixels.

Several implementations of space-variant visual sensors have been presented in the past. They include custom-designed CCD/CMOS sensors [19, 9], digital warping [24, 10, 16], or a combination of wide/tele cameras [25, 21], but suffer from problems such as continuity, efficiency or co-axial parallelism.

Our approach avoids these problems by an alternative approach pioneered by Suematsu[23]: designing a new optics. This method can deal with the optical projection process which cannot be fully treated by the two dimensional methods such as CCD/CMOS design or the warping method. This becomes critical when we want to achieve a wide view angle. Even if we use the space variant CCD, we must use some wide angle lens, which generally deviates substantially from the standard (non-distorted) projection. Therefore, if we ignore the optical process, we cannot obtain a desired image. Integrating the optical process and the 2D image transformation is very important in achieving a foveated wide angle vision.

![Figure 3: The camera projection model. A 3D point \( \mathbf{X} = (X, Y, Z)^T \) in the left camera referential \( \mathbf{R}^l \) has for incidence vector \( \mathbf{\xi} = (\Theta, \Phi)^T \) and projects into \( \mathbf{x} = (x, y)^T \) on the image plane with polar coordinates \( (r(\Theta), \pi/2 - \Phi)^T \).](image)

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**Table 1: Dynamic performance of ESCHeR**

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<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Pan</td>
<td>200°</td>
<td>140°/s</td>
<td>4000°/s²</td>
<td>0.0044°</td>
</tr>
<tr>
<td>Elev.</td>
<td>090°</td>
<td>350°/s</td>
<td>14000°/s²</td>
<td>0.0145°</td>
</tr>
<tr>
<td>Verg.</td>
<td>100°</td>
<td>400°/s</td>
<td>16000°/s²</td>
<td>0.0125°</td>
</tr>
</tbody>
</table>

**Table 2: Dimension of ESCHeR**

<table>
<thead>
<tr>
<th>Width</th>
<th>Height</th>
<th>Depth</th>
<th>Baseline</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>222 mm</td>
<td>187 mm</td>
<td>160 mm</td>
<td>180 mm</td>
<td>2.0 kg</td>
</tr>
</tbody>
</table>
Our lens is carefully designed to provide a projection curve which has useful intrinsic properties which help computer vision algorithms\cite{12}, unlike \cite{23}. A projection curve maps the incident angle $\Theta$ of a sight ray entering the lens system to an image height $r(\Theta)$ on the CCD surface (Figure 3).

The curve seamlessly combines the high resolution fovea and low resolution periphery in a single special optics, with a 120° field of view and the maximum magnification of 7.7 in the fovea versus the periphery.

### 3 Disparity and velocity cues for robust tracking

Aiming towards versatile human-robot interaction, we would like at a first to provide the robot with the ability to detect and track, without even recognizing the content of what it sees. The target should be an open-ended assortment of moving objects (human heads, toys, etc.), with possibly deformable shapes (hands or body limbs). And the background would be highly cluttered scenes (usual laboratory environments). A model based or template matching strategy would then be quite costly and even inappropriate. As an alternative, we demonstrate in the present section how the integration of optical flow and binocular disparity, two simple cues commonly found in biological visual systems and well-known in image processing, can lead to very robust performance in the tracking of arbitrary targets in complex environment.

#### 3.1 Velocity Cues

The detection and pursuit of moving objects in the scene can be performed by making the distinction, in the motion field, between velocity vectors produced by the camera egomotion and those inferred by independent motion. In the case of ESChER, since the body is fixed to the ground, the camera movements are constrained by the mechanical configuration of the head. However, because of the high distortions introduced by the foveated wide-angle lens, a simple background flow subtraction method \cite{2} cannot be directly implemented. We will demonstrate in the following parts that the flow produced by the camera egomotion can be approximated in the velocity domain by an ellipsoid distribution, whose center coordinates, orientation and axis length can be directly derived from the instantaneous rotation vector of the camera. We will illustrate our argument by examples of real flow fields taken on our lens prototype, and show how the ellipsoid model can be used to segment independent motion from the camera egomotion.

**Flow extraction.** Following an extensive review on the performance of optical flow algorithms \cite{1}, we decided to implement a gradient-based method with local smoothness constraints that is inspired from the work of \cite{13} on stereo vision systems, because of its computational simplicity and the good results it yields in comparison with other techniques. We also added two modifications to the proposed scheme: an IIR recursive filter introduced by \cite{6} for computing a reliable time gradient while respecting real-time constraints.
and a Bayesian approach suggested by [22] for estimating flow reliabilities. Our current implementation extracts $36 \times 36$ flow vectors with confidence values from $324 \times 324$ pixels at frame rate.

**Egomotion flow.** To determine the motion field generated by the camera, let us consider a point $X = (X, Y, Z)^T$ of the static scene. The image motion $v_c$ at position $x$ corresponding to $X$ can be written as

$$v_c = M_x \Omega.$$ 

where $\Omega$ is the angular velocity of the camera motion, with the set of matrix $M_x$ being only dependent on the position $x$ on the image and the projection function (1). Translational component of the camera is ignored because the base of ESCHeR is static, in our setup.

$M_x$ can be expressed from the incidence vector $\xi$ as

$$M_x = \begin{pmatrix} S_\phi C_\phi (r/T_\theta - r') & C_\phi^2 r'/T_\theta + S_\phi r/T_\theta & -S_\phi r \cr S_\phi^2 r'/T_\theta + C_\phi^2 r/T_\theta & S_\phi C_\phi (r/T_\theta - r') & -C_\phi r \end{pmatrix}$$

where we have defined $r = r(\Theta)$ and $r' = dr(\Theta)/d\Theta$ and $T_\theta = \tan(\Theta), S_i = \sin(\theta_i)$ and $C_i = \cos(\theta_i)$ for $i \in \{l, e, p\}$. Fig. 6 shows the difference between the theoretical egomotion field obtained from (2) and the real one recovered with a gradient based optical flow algorithm [13] implemented on our foveated wide-angle system.

![Image of simulated and recovered egomotion fields](image_url)

**Egomotion distribution.** To segment out objects moving independently of the background, [15] suggested to subtract the component $v_c$ from each corresponding vector $v$ of the motion field. This method, while accurate in theory, requires unfortunately an accurate calibration of the mechanical and optical system in order to achieve robustness in the segmentation. However, we can see in Fig. 6 that the egomotion flow field in the velocity domain roughly follows an ellipsoid distribution. In fact, from (2), and due to the symmetry in the radial distribution of the resolution of our lens, the mean of the distribution can be derived from the instantaneous motion $\Omega$ as

$$\bar{v} = \frac{1}{N} \sum_x M_x \Omega = \begin{pmatrix} 0 & \mu & 0 \\ \mu & 0 & 0 \end{pmatrix} \Omega$$

where we have defined the constant

$$\mu = \frac{1}{N} \sum_x [S_\phi^2 r' + C_\phi^2 r/T_\theta]$$

The covariance matrix of the distribution, defined as

$$\Gamma = \frac{1}{N} \left( \sum (u - \bar{u})^2 \sum (v - \bar{v})^2 \right),$$

can also be simplified due to the symmetric properties of our lens and takes the simple form

$$\Gamma = \begin{pmatrix} \alpha \Omega_x^2 + \beta \Omega_y^2 + \gamma \Omega_z^2 & \delta \Omega_x \Omega_y & \delta \Omega_x \Omega_z \\ \delta \Omega_y \Omega_x & \beta \Omega_y^2 + \alpha \Omega_x^2 + \gamma \Omega_z^2 & \delta \Omega_y \Omega_z \\ \delta \Omega_z \Omega_x & \delta \Omega_z \Omega_y & \delta \Omega_z \Omega_y \end{pmatrix}$$

While the constant $\alpha, \beta, \gamma$ and $\delta$ can be derived directly from (1), it is possible to implement a quick and automatic calibration procedure to determine their real values on our implementation. It is done by rotating at various speeds the cameras in front of a static, highly textured background and computing the flow mean and covariance. By setting the camera configuration such as only one component of $\Omega$ is non-null at a time, a simple linear regression can easily provide the desired coefficients. Fig. 7 shows the regression used to determine the parameters $\mu, \alpha$ and $\beta$ while Table 3 summarizes the theoretical and real coefficients of the egomotion distribution.

<table>
<thead>
<tr>
<th>Coef</th>
<th>Unit</th>
<th>Theor. val.</th>
<th>Calib. val.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu$</td>
<td>pix/deg</td>
<td>9.05</td>
<td>8.60</td>
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<tr>
<td>$\alpha$</td>
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<td>$\beta$</td>
<td>pix$^2$/deg$^2$</td>
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<td>$\gamma$</td>
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<td>1.87</td>
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<td>$\delta$</td>
<td>pix$^2$/deg$^2$</td>
<td>26.16</td>
<td>17.63</td>
</tr>
</tbody>
</table>

Table 3: Egomotion flow parameters
Figure 7: Calibration of the egomotion distribution coefficients. The left camera rotates horizontally at various speed ($\Omega_X = 0, \Omega_Y = \theta_1, \Omega_Z = 0$) in front of a textured and static background, and the parameters $\mu, \alpha$ and $\beta$ are computed from simple linear regression using the covariance matrix $\Gamma$. The coefficient $\gamma$ and $\delta$ are computed using a similar method.

Segmentation. From the covariance matrix $\Gamma$ computed in (7), it is possible to extract two Eigen vectors $v_1$ and $v_2$ with norm respectively equal to the square root of the eigenvalues $\lambda_1$ and $\lambda_2$ of $\Gamma$. Then, given a vector $v$ of the motion field, we can define the distance

$$l(v) = \sqrt{\frac{|(v - \bar{v}) \cdot v_1|^2}{|v_1|^2} + \frac{|(v - \bar{v}) \cdot v_2|^2}{|v_2|^2}},$$

and, approximating the egomotion flow in the velocity domain with a Gaussian distribution, compute the probability of independent motion as

$$P(v) = 1 - e^{-\frac{d(v)^2}{2\sigma^2}}$$

where $\sigma$ is a constant that can be adjusted manually to determine how strict the membership to the ellipsoid model is. The results of the flow segmentation during a tracking sequence are presented in Figure 8.

3.2 Disparity cues

Disparity estimation plays a key role in our visual system. It not only ensures that we are fixating on the same object with both eyes, but provides also some cues for depth perception and focus control. The recent introduction of dynamic vergence using binocular disparities [4, 17] has significantly improved the performance of stereo active vision systems. We describe in this section a method based on the Fourier shift theorem to recover spatial displacements from phase difference which is well adapted to our application [20]. To cope with the local characteristics of disparity in stereo images, the algorithm uses local phase information from the output of complex band-pass filters instead of the global phase with Fourier transformations [27]. The method is robust, produces dense maps and is very well suited for real-time implementation.

The Fourier shift theorem. If we let $l(x)$ and $r(x)$ be two one-dimensional signals, one being the shifted version of the other, e.g., $l(x) = r(x - \Delta x)$, the Fourier shift theorem states that their respective Fourier transforms $L(\omega)$ and $R(\omega)$ fulfill the relation

$$L(\omega) = e^{j\omega\Delta x} R(\omega)$$

where $j^2 = -1$. Therefore, for any given frequency $\omega$ such as $|L(\omega)| > 0$ (or similarly $|R(\omega)| > 0$), we can establish between the phase of the two signals the relation

$$\phi_l(\omega) = \phi_r(\omega) + \omega \Delta x$$

with the notation $\phi_l(\omega) \equiv arg(I_l(\omega))$. If $\omega \neq 0$, the global shift $\Delta x$ can then be recovered with

$$\Delta x = \frac{[\phi_l(\omega) - \phi_r(\omega)]_{2\pi}}{\omega}$$

where $[\phi]_{2\pi}$ denotes the principal part of $\phi$ that lies between $-\pi$ and $\pi$.

From phase to disparity. (12) demonstrates that the disparity can be directly derived from the phase and frequency of the signals. This approach exhibits clear advantages over correspondence and correlation methods, but comes not without a few drawbacks. On one hand phase is amplitude invariant, hence varying illumination conditions between the left and right images do not perturb significantly the computation. Local phase is also robust against small image distortions [7], which makes it very suitable to handle the small optical deformations of our space-variant resolution in the foveal area (The disparity is only computed in the
Moreover, this method produces dense disparity maps and requires no explicit feature detection or matching process.

On the other hand, the Fourier shift theorem cannot be directly applied for the analysis of stereo images, at least not in its present from: first, it requires a global shift between the two signals, whereas pixel displacements in a stereo pair are fundamentally local. Intuitive solutions, like applying the Fourier transform on small patches of the images, have been suggested [26], but the computational complexity becomes important and the precision decreases drastically with the size of the local window. A more interesting approach is to recover the local phase and frequency components in the signal using the output of complex-valued band-pass filters [20]. Fig. 9 shows a binocular disparity map obtained from the phase information after convolution with a complex-valued Gaussian difference filter [27].

Figure 9: Disparity estimation. The original stereo pair (left), and the phase-based disparity map (right).

The horopter. By definition, any point of zero disparity projects onto left and right image points with identical coordinates. The set of such points, called the horopter, generates a surface passing through the fixation point (Fig. 10). By filtering points of zero disparity, we can then easily segment a target lying in the horopter from the background and estimate its position.

3.3 Zero-disparity filtering

In order to extract the dominant object in the horopter, we apply at first a Symmetric Nearest Neighbor (SNN) filter [8] on the disparity map to smooth homogeneous areas while enhancing region boundaries. Then, a region growing algorithm groups connected regions with homogeneous disparity. Meanwhile, the cluster with the best confidence is selected as the target mask.

Figure 11: Zero-disparity filtering. The disparity map from Figure 9 is convolved with a SNN filter to smooth homogeneous areas and enhance region boundaries (left). A region growing then group connected components of the map (right) and the cluster which maximize confidence and low disparity is picked as the target mask in the horopter (right).

4 Control

4.1 Cue integration

Using the centroid of the segmentation masks presented in Fig. 8 and Fig. 11, it is straightforward to see that we can easily obtain estimates on the target position, velocity and disparity.

The target position can be estimated as follows:

$$x_t = \frac{\mu_v x_v + \lambda \mu_d x_d}{\mu_v + \lambda \mu_d},$$

(13)

where $x_v$ is the position estimation from the velocity cue, $x_d$ is the position from disparity, and $\mu_v$ and $\mu_d$ are respective confidence values.

In general, the centroid computation may not be valid if for example several targets appear on the field of view. However, it is perfectly justified in our case due to the space-variant properties of our lens. In fact, when an object is followed, it occupies the main portion of the image to due the magnification factor in the fovea and thus the tracking is not perturbed by other objects in the field of view. Fig. 12 summarizes the process that combines velocity and disparity information to obtain the target position and velocity in both images, as well as its binocular disparity.

Figure 13 shows an example of cue integration. A moving object is being tracked while the head is motionless (passive tracking). This condition is deliberately chosen to emphasize the target velocity and disparity change, so that the effect of cue integration is most apparent from the images. The top row shows the original image sequence from the right camera (5
Figure 12: Combining disparity and velocity information to obtain the target position and velocity in both left and right images, as well as its binocular disparity.

Figure 13: Cue integration.

images out of 30 sampled every 6 frames for a total of 1 second of tracking). The middle row shows the velocity segmentation map, with the centroid \( x_v \) plotted as a dot while the length of the vertical line on the side is proportional to the confidence \( \mu_v \) of the velocity segmentation. The bottom row shows the zero-disparity filtering results, with the centroid \( x_d \) plotted as a dot while the length of the vertical line is proportional to the confidence \( \mu_d \) of the disparity segmentation. The dot plotted on the top images shows the final target position \( x_t \) as computed in Equation (13), while the arrow shows the target velocity \( \dot{x}_t \) obtained from velocity segmentation. At first the target (a toy car) is moving outside the horopter, so the confidence \( \mu_v \) is high while \( \mu_d \) is low since the cameras are not properly verged, which means that the target position is given by the velocity segmentation. The target then progressively enters the horopter area and both \( \mu_v \) and \( \mu_d \) have high values. As the target slows down until a complete stop in the horopter area, \( \mu_v \) decreases while \( \mu_d \) stays high, hence the target position is given by disparity segmentation. As shown by the accurate position of the dot in the original image sequence, this framework ensures that the target is properly tracked even if one or the other detection method fails. However, it is important to note that this method is unable to locate motionless targets outside the horopter area, e.g., when both methods are ineffective.

4.2 Basic attentional mechanism

Three main behaviors are implemented in the current tracking system. (1) A observation behavior that rotates the head randomly until it detects some motion activity in the scene. (2) A saccade behavior that quickly redirect the gaze when a moving object is detected far from the center of the retina. (3) A smooth pursuit behavior that follows objects in the fovea with the disparity and velocity cues described previously and fusing those information with a Kalman filter. Fig. 14 summarizes the coordination mechanism that switch the system between those three behaviors.

Figure 14: Control mechanism for switching between observation, saccade and smooth pursuit behaviors. When there is no independent motion activity in the scene over a certain amount of time (a fixed threshold \( P_{\text{min}} \)) the head starts moving randomly. It then saccades quickly when a moving object is detected in the periphery (a fixed radius \( r_p \) defines the boundary between the peripheral and foveal areas of the image). Once the target is acquired in the fovea, the systems uses both velocity and disparity information for the smooth pursuit if the moving object.

5 Implementation and performances

The hardware used in our experiment consists of a Datacube LynxOS system with two maxvideo 250 boards for image acquisition and pipeline processing, as well as a set of four INTEL i860 chips for floating point operation (Fig. 15). This image processing unit is connect through transputer links to the servo controller, a set of two INMOS T805 transputers which operates the four DC motors of ESCRHeR.

The optical flow algorithm used in the motion segmentation process is a gradient based with local constraint method [13] combined with an IIR recursive filter [6] for time smoothing with low latencies. The flow field is computed in stereo at frame rate (30Hz) on a 324x324 area sub-sampled every 9 pixels around the fovea on two i860 chips. The phase-based disparity filter is computed as well at frame rate on a single i860 chip using the derivatives filters suggested in [14].
While no benchmarks are available to compare the performances of real-time tracking systems, our implementation has proven capable of tracking at frame rate human body parts such as hands and heads moving with speed up to 80 deg/s over cluttered backgrounds. The proposed algorithm is robust for well contrasted targets, but the performances decrease when the contrast is low and gradient-based algorithms not very responsive. Lack of performances is also experienced in the target acquisition mechanism because of the over-simplification of the saccade to pursuit transition mechanism. However the proposed method looks very effective for generating micro saccade which quickly re-center the target when it lies slightly out of the fovea.

6 Conclusion

Learning by imitation and human-robot interaction are to play a fundamental role in the development of intelligent behaviors for autonomous robots. In this paper, we have demonstrated how, by using two independent cues commonly found in biological systems, we could provide a robot with the crucial skill of tracking objects, without a-priori knowledge of shape or texture, over cluttered scenes. The implemented system, while taking advantage of the mechanical and optical properties of ESCHeR, our active vision system equipped with space-variant sensors, has proven capable of tracking human body parts such as hands and heads in real-time over complex backgrounds.

However, the proposed system still lack of performances in certain areas. The transition between saccade and smooth tracking for example needs to be more carefully designed. In our current implementation, the centroid of the segmented motion is used to initiate the saccade. Since this is a very rough measurement, and since we rely on the theoretical model of our lens to convert image coordinates into angular measures, the target position after the saccade sometimes exceeds the maximum range of disparity allowed by our filter and thus the smooth tracking which combine target position from zero-disparity filtering and velocity estimation from motion segmentation can not be properly initialized. This could be solved by extending the maximum range of disparity of the phase-based algorithm (with a multi-scale approach for example), or by refining the saccade control through the learning of saccade maps [3].

The next direction for our research will be to investigate how the purely reflexive (bottom-up) behavior which is currently implemented could be combined with a top-bottom control scheme so that the robot can evolves from the state of observer to a more interactive agent in the environment. This should lead to a deeper understanding of some fundamentals of the action-perception paradigm which is critical for the development of intelligent and autonomous robots evolving in complex and dynamic environments.

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References


