

Constrained Homography Estimation and Geometric Target Recovery for Vision-Based Mobile Robot Navigation

Wenhao Fu¹, Hicham Hadj-Abdelkader², Lamri Nehaoua³, and Hichem Arioui⁴

Abstract—This paper addresses vision-based navigation when a planar visual target completely leaves the camera field of view during obstacle circumnavigation. Two geometric components are proposed. First, the planar motion of a ground robot and the vertical orientation of the target are exploited to derive a constrained plane-induced homography with four effective degrees of freedom. A minimal solver requiring only two point correspondences is embedded in RANSAC, thereby reducing the number of random samples required in the presence of mismatches and partial occlusions. Second, when the target becomes unavailable, the plane structure estimated at the last valid observation is combined with the ego-motion accumulated during the visual blackout to predict the current homography. The unknown translation scale cancels provided that the ego-motion estimates share a locally constant scale factor. The predicted target direction is then used for active re-acquisition after the obstacle has been cleared. The methods are demonstrated on the differential-drive robot LINA in an indoor navigation experiment involving a prolonged target loss. Obstacle avoidance is provided by a previously published B-spline reactive controller and is used here only as the navigation support that generates the challenging camera motion.

Keywords—visual servoing, homography estimation, target loss, mobile robot navigation.

I. INTRODUCTION

Visual servoing controls robot motion directly from image measurements [1]. For a wheeled mobile robot, image-based control can guide the platform toward a pose represented by a reference view, without requiring a global metric map. Its practical deployment in cluttered environments nevertheless raises two coupled difficulties. The robot must avoid previously unknown obstacles, and the bypass motion may push the visual target partly or completely outside the camera field of view. When all target features disappear, conventional image-based visual servoing (IBVS) loses the feedback signal on which its control law relies.

Most visibility-aware visual-servoing methods are preventive. Image-space path planning, field-of-view constraints, switching strategies, and model predictive control seek to retain enough features throughout the motion [1], [7]. Corrective methods instead tolerate a loss and use prediction or active search to recover the target [8], [9]. Complete and

prolonged loss remains more difficult than partial occlusion because no current image measurement is available to correct accumulated prediction errors.

This work considers a differential-drive robot observing a vertical planar target with a calibrated monocular camera. The main idea is to use the same projective geometry both before and during target loss. Before the loss, the robot-target configuration induces a structured homography that can be estimated from only two correspondences. During the loss, the last valid plane estimate is propagated with the relative ego-motion to predict the target configuration, including when its projection lies outside the image.

In this paper, we present three key elements of the proposed framework.

- A constrained homography model is derived for planar camera motion and a vertical target. Since the model has four effective degrees of freedom, a minimal two-correspondence solver can be used within RANSAC.
- A geometric prediction method reconstructs the plane-induced homography during complete target loss. It combines the plane structure recorded at the last valid observation with the relative ego-motion and does not require the absolute target depth.
- The estimator and recovery method are integrated into a complete navigation sequence comprising visual servoing, obstacle bypass, visual blackout, active re-acquisition, and resumption of measured IBVS.

The obstacle-avoidance controller itself is not a contribution of this paper. It is the B-spline reactive method previously introduced in [10], and is retained only to generate the bypass motion in the experimental scenario.

The remainder of the paper is organised as follows. Section II reviews related work. Section III presents the system and its operating modes. Section IV derives the constrained homography and the two-point RANSAC estimator. Section V develops the prediction and re-acquisition method. Section VI reports the experimental demonstration, and Section VII concludes the paper.

II. RELATED WORK

Plane-induced homographies are generally estimated from at least four point correspondences. In the presence of mismatches, the direct linear transform is commonly combined with RANSAC to obtain a robust estimate. However, the number of random trials required by RANSAC increases rapidly with the size of the minimal sample, which has motivated the development of minimal solvers that exploit

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additional geometric constraints. Recent studies have therefore continued to investigate constrained and low-cardinality homography estimation methods [5], [6]. Unlike the general camera-pair configuration considered by most existing approaches, the ground-mobile-robot configuration addressed in this work constrains both the camera motion and the orientation of the observed plane. These assumptions lead to a sparse homography structure that can be estimated from only two point correspondences.

Target visibility is another important issue in visual servoing. Most existing approaches attempt to prevent visual-feature loss by maintaining the features inside the camera field of view. Predictive visual servoing, for example, incorporates state and control constraints over a finite prediction horizon [7], whereas other methods modify the visual task or adapt the camera trajectory to reduce the risk of occlusion. When visibility loss cannot be prevented, feature locations may be propagated over short time intervals, or an active camera motion may be used to search for the target [8], [9]. Nevertheless, predictions based on independently propagated image features are generally sensitive to drift when visual measurements remain unavailable for an extended period. The approach proposed here instead propagates a single plane-induced homography. It therefore maintains the projective consistency of the complete planar target during a total visual blackout, rather than predicting each image point separately.

The experimental scenario also involves reactive obstacle avoidance for a mobile robot. Existing obstacle-avoidance methods can broadly be divided into planning-based approaches, which compute a collision-free path from a model of the environment, and reactive approaches, which directly adapt the robot motion from local sensor measurements. In the experiments reported in this paper, laser clusters are represented by smooth convex B-spline boundaries and followed using a safety envelope, according to the method introduced in our previous work [10]. That published framework includes laser-data segmentation, convex-boundary extraction, B-spline fitting, boundary following, and continuous switching between the obstacle-avoidance and visual tasks. These components are not contributions of the present paper. They are used here as an application support to generate a realistic obstacle-circumnavigation motion involving substantial viewpoint changes and, potentially, the complete disappearance of the visual target. This challenging motion provides the operating conditions required to evaluate the proposed constrained homography estimator and geometric target-recovery strategy.

III. SYSTEM AND OPERATING MODES

The platform is a differential-drive robot equipped with a calibrated monocular camera, a planar 2-D laser range finder, and wheel encoders. The camera detects and tracks a textured planar target. The laser supplies local obstacle measurements, whereas the encoders provide the relative ego-motion used during a visual blackout.

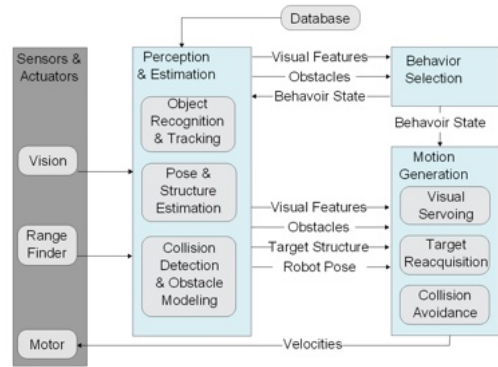


Fig. 1. Navigation architecture. The contributions of this paper are the constrained homography estimator and the geometric prediction/re-acquisition module.

The control architecture in Fig. 1 contains four main blocks: perception, behaviour selection, motion generation, and robot actuation. A finite-state machine selects one of the following modes: (i) measured visual servoing, (ii) obstacle bypass while the target remains visible, (iii) obstacle bypass under complete target loss, (iv) active target re-acquisition, and (v) stop. Collision avoidance has priority while the robot remains inside the obstacle safety region. The proposed homography estimator operates whenever target correspondences are available. The geometric predictor is activated at the last valid target observation and remains active until reliable correspondences are detected again.

The state transitions are event driven. The nominal visual-servoing mode is left when the laser safety envelope is reached. If the target remains visible, visual measurements continue to update the plane estimate during the bypass. A loss event is declared only when the number of geometrically consistent correspondences falls below the minimum required for a valid model over several consecutive frames; this temporal confirmation avoids switching because of a single poor image. The last accepted homography and plane parameters are then frozen and the predictor is initialised. The re-acquisition state is entered only after the obstacle controller signals that the safety envelope has been cleared. Finally, measured IBVS is resumed after a newly detected target model passes both the RANSAC consensus test and a consistency test with the predicted target region. This separation prevents a premature return to visual control because of isolated false matches.

IV. CONSTRAINED TWO-POINT HOMOGRAPHY ESTIMATION

A. Geometric assumptions and reduced model

Consider a static vertical planar target observed by a calibrated pinhole camera rigidly attached to a robot moving on a horizontal floor. Roll and pitch variations are assumed negligible over the considered motion. In the camera convention used here, the xz plane is parallel to the ground. Consequently, the plane normal has the form $\mathbf{n} = [n_x \ 0 \ n_z]^T$, while the camera translation also lies in the xz plane and the relative rotation is a yaw rotation.

For two camera views of the same plane, the normalised plane-induced homography is

$$\mathbf{H} = \mathbf{R} + \frac{1}{d} \mathbf{t} \mathbf{n}^\top, \quad (1)$$

where d is the plane distance in the first camera frame. Under the stated motion and plane constraints, (1) becomes

$$\mathbf{H} = \begin{bmatrix} h_{11} & 0 & h_{13} \\ 0 & h_{22} & 0 \\ h_{31} & 0 & h_{33} \end{bmatrix}. \quad (2)$$

The matrix contains five non-zero coefficients but only four effective degrees of freedom because a homography is defined up to a non-zero scale. The value h_{22} may be used for scale normalisation when it is safely separated from zero.

B. Minimal two-correspondence solver

Let $\mathbf{x}_1 = [x_1 \ y_1 \ z_1]^\top$ and $\mathbf{x}_2 = [x_2 \ y_2 \ z_2]^\top$ be corresponding homogeneous image points in normalised coordinates. The relation $\mathbf{x}_2 \times \mathbf{H} \mathbf{x}_1 = \mathbf{0}$ yields two independent equations. With

$$\mathbf{h}_r = [h_{11} \ h_{13} \ h_{22} \ h_{31} \ h_{33}]^\top, \quad (3)$$

each match contributes

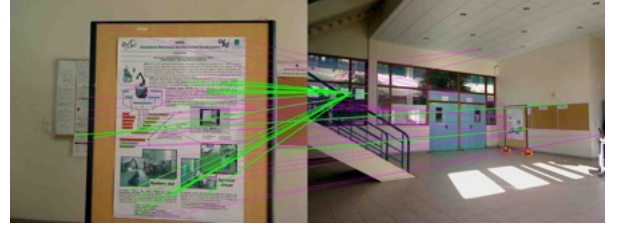
$$\mathbf{A}_r(\mathbf{x}_1, \mathbf{x}_2) = \begin{bmatrix} 0 & 0 & -y_1 z_2 & x_1 y_2 & z_1 y_2 \\ x_1 z_2 & z_1 z_2 & 0 & -x_1 x_2 & -z_1 x_2 \end{bmatrix}. \quad (4)$$

Two correspondences provide four independent constraints and determine $\mathbf{h}_r$ up to scale from the right singular vector associated with the smallest singular value of the stacked matrix. Image coordinates are normalised before estimation. Samples are rejected when the two points are too close in either image or when the stacked system is ill-conditioned. After consensus has been found, the homography is re-estimated from all inliers and optionally refined by minimising the symmetric transfer error.

C. Observability and degenerate configurations

The reduced parameterisation does not make every pair of correspondences informative. Two matches located too close to one another provide nearly redundant constraints, while points close to the horizon of the normalised image may amplify measurement noise. Degeneracy is detected from the singular-value ratio of the stacked matrix. A sample is rejected when the second-smallest singular value becomes too small with respect to the largest one, indicating that the null space is not uniquely defined in practice. In addition, the recovered model must preserve the orientation of the target and map the selected points to finite image locations.

These tests are particularly important for a two-point solver because a small sample offers little internal redundancy. They are inexpensive, however, and can be applied before model scoring. Once a consensus set has been obtained, redundancy is restored by re-estimating all five non-zero entries from the complete inlier set. The constrained model may also be used only for hypothesis generation, followed by a nonlinear refinement of the full homography when slight roll, pitch, or target-orientation errors must be absorbed.



(a) General four-point RANSAC.



(b) Constrained two-point RANSAC.

Fig. 2. Correspondences accepted (green) and rejected (pink) under a large viewpoint change. The constrained estimator uses the planar-motion and vertical-target assumptions.

D. RANSAC integration

For a desired success probability p , inlier probability w , and minimal sample size m , the standard RANSAC iteration bound is

$$N = \frac{\log(1-p)}{\log(1-w^m)}. \quad (5)$$

For example, with $p = 0.99$ and $w = 0.5$, a two-point sample requires about 17 trials, compared with about 72 trials for a four-point sample. The conventional four-point estimator remains geometrically valid, but it does not exploit the structure of (2) and therefore uses larger minimal subsets.

A candidate model is scored using the symmetric transfer error

$$d_{\text{sym}}^2 = \|\mathbf{x}_2 - \pi(\mathbf{H} \mathbf{x}_1)\|_2^2 + \|\mathbf{x}_1 - \pi(\mathbf{H}^{-1} \mathbf{x}_2)\|_2^2, \quad (6)$$

where $\pi(\cdot)$ denotes homogeneous normalisation. A match is accepted when d_{sym} is below a fixed pixel-domain threshold after undoing the coordinate normalisation. The threshold is shared by the two-point and four-point baselines so that the comparison reflects the model structure rather than a different inlier definition.

The estimator follows four steps: random selection of two matches, construction and validation of the constrained hypothesis, consensus scoring with (6), and final re-estimation from all inliers. The iteration count is updated online from the best observed inlier ratio, with a prescribed upper bound for real-time operation. Figure 2 illustrates a difficult image pair for which the reduced model rejects inconsistent correspondences and retains the target matches.

V. GEOMETRIC RECOVERY UNDER COMPLETE TARGET LOSS

A. Frames and last valid observation

Let $\mathcal{F}_r$ denote the reference camera frame, $\mathcal{F}_\ell$ the frame of the last valid target observation, and $\mathcal{F}_k$ the current camera frame during the loss interval. While the target is visible, the homography between successive views is estimated using the

method of Section IV. Its decomposition provides a relative rotation, a translation scaled by the plane distance, and a plane normal [12].

Immediately before loss, homography decomposition yields $(\mathbf{R}_H, \mathbf{t}_H, \mathbf{n}_\ell)$, where $\mathbf{t}_H$ denotes the translation divided by the plane distance d_ℓ . Over the same short interval, the ego-motion estimator provides $(\hat{\mathbf{R}}, \lambda \hat{\mathbf{t}})$, where λ is either one for metric odometry or an unknown locally constant factor for up-to-scale motion. Since the two translations represent the same displacement,

$$\lambda \hat{\mathbf{t}} = d_\ell \mathbf{t}_H, \quad d_\ell = \lambda \frac{\|\hat{\mathbf{t}}\|}{\|\mathbf{t}_H\|}. \quad (7)$$

The plane normal $\mathbf{n}_\ell$ and the ratio $\rho = \|\mathbf{t}_H\|/\|\hat{\mathbf{t}}\|$ are stored at the last valid observation.

B. Closed-form homography prediction

During the blackout, let $({}^k\hat{\mathbf{R}}_\ell, \lambda {}^k\hat{\mathbf{t}}_\ell)$ be the ego-motion accumulated from $\mathcal{F}_\ell$ to $\mathcal{F}_k$. Assuming a static target and locally constant scale, the homography from the last visible view to the current view is predicted as

$$\begin{aligned} {}^k\hat{\mathbf{H}}_\ell &= {}^k\hat{\mathbf{R}}_\ell + \frac{\lambda {}^k\hat{\mathbf{t}}_\ell \mathbf{n}_\ell^\top}{d_\ell} \\ &= {}^k\hat{\mathbf{R}}_\ell + \rho {}^k\hat{\mathbf{t}}_\ell \mathbf{n}_\ell^\top. \end{aligned} \quad (8)$$

The unknown factor λ cancels because it is common to the stored scale relation and to the motion accumulated during the loss. This cancellation is valid only while that scale remains locally consistent. The predicted homography from the reference view to the current view is then obtained by composition with the last valid reference-to-current homography,

$${}^k\hat{\mathbf{H}}_r = {}^k\hat{\mathbf{H}}_\ell {}^\ell\mathbf{H}_r. \quad (9)$$

This composition is preferable to repeatedly multiplying frame-to-frame homographies during the blackout because only the ego-motion is integrated; the projective plane information remains anchored at the last reliable visual observation.

The predicted target corners may lie outside the image. They are therefore used as geometric bearings rather than as virtual measurements. In particular, no claim of closed-loop visual feedback is made while the camera receives no target observation.

C. First-order error propagation

Let $\delta\hat{\mathbf{R}}$ and $\delta\hat{\mathbf{t}}$ denote perturbations of the accumulated ego-motion, and let $\delta\mathbf{n}_\ell$ be the error in the stored plane normal. Treating ρ as locally constant and neglecting second-order terms gives

$$\delta\mathbf{H} \approx \delta\hat{\mathbf{R}} + \rho \left(\delta\hat{\mathbf{t}} \mathbf{n}_\ell^\top + \hat{\mathbf{t}} \delta\mathbf{n}_\ell^\top \right). \quad (10)$$

Thus, rotational drift, translational drift, and plane-normal uncertainty all contribute to prediction error. The rotational term directly changes the predicted bearing, whereas translation and plane-normal errors are coupled through the rank-one term. A distant plane reduces the influence of translation,

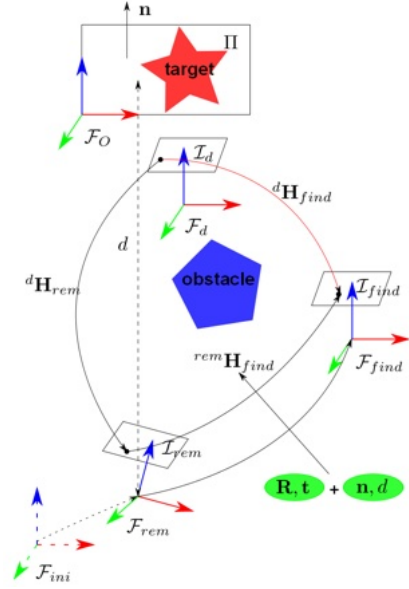


Fig. 3. The plane structure stored at the last valid observation is combined with the accumulated ego-motion to predict the target homography during complete visual loss.

while an inaccurate normal can distort all predicted target points coherently. Equation (10) therefore explains why the centroid direction may remain useful for re-acquisition even when the individual predicted corners have already accumulated a noticeable projective error. This motivates keeping the blackout interval short and reducing translation during active re-acquisition.

D. Prediction-based steering and re-acquisition

When the target is visible, the angular velocity is generated by the standard IBVS law. Let $\mathbf{u} = [v \ \omega]^\top$, let $\mathbf{v}_c = \mathbf{J}\mathbf{u}$ be the camera velocity, and let $\mathbf{L}_{s,v}$ and $\mathbf{L}_{s,\omega}$ denote the interaction-matrix columns associated with linear and angular robot motion. For prescribed v ,

$$\omega_{go} = -\mathbf{L}_{s,\omega}^+ (\gamma \mathbf{e} + \mathbf{L}_{s,v} v), \quad (11)$$

where $\mathbf{e} = \mathbf{s} - \mathbf{s}^*$.

During obstacle bypass, collision avoidance remains the primary command. The predictor maintains only an estimate of the target direction. Once the obstacle is cleared, the linear speed is reduced or set to zero and the robot is rotated toward the predicted target centroid. If x_c is its predicted horizontal normalised coordinate,

$$\Delta\theta = \arctan(-x_c), \quad \omega_h = -\gamma_h \Delta\theta, \quad (12)$$

with the sign adapted to the camera convention. Re-acquisition is declared only after a sufficient number of geometrically consistent matches has been accepted by the two-point RANSAC. Predicted points are then discarded and measured IBVS (11) resumes.

VI. EXPERIMENTAL DEMONSTRATION

A. Platform and scenario

Experiments were conducted with the differential-drive robot LINA, shown in Fig. 4. A 55.8×73.5 cm textured



Fig. 4. Differential-drive robot LINA.

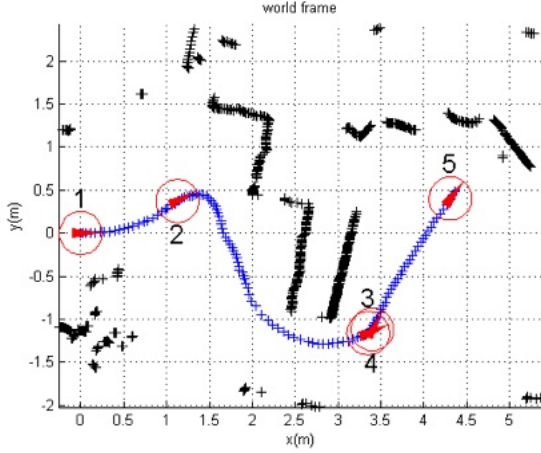


Fig. 5. Executed trajectory (blue), representative milestones (red), and laser-detected obstacles (black).

poster was used as the planar target. A box-like obstacle was placed between the initial robot pose and the target so that the bypass forced the target outside the camera field of view. The four poster corners defined the IBVS features. Laser-based collision avoidance used the previously published controller of [10].

B. Navigation sequence

Figure 5 shows the executed trajectory and five representative instants: (1) measured visual servoing, (2) activation of obstacle avoidance, (3) complete target loss, (4) active re-acquisition after clearing the obstacle, and (5) target re-detection followed by measured IBVS. The archived sequence contains 721 images acquired at approximately 10 Hz. The target is absent from the camera image for more than ten seconds, which is long enough for direct image-space extrapolation to become unreliable.

Figure 6 presents the camera and laser data at the same instants. At instant 3 the target has completely disappeared. The predicted homography is nevertheless propagated from the last valid plane estimate. After the obstacle is cleared, the re-acquisition command turns the robot toward the predicted bearing. At instant 5, visual correspondences are again available and the controller returns to measured IBVS.

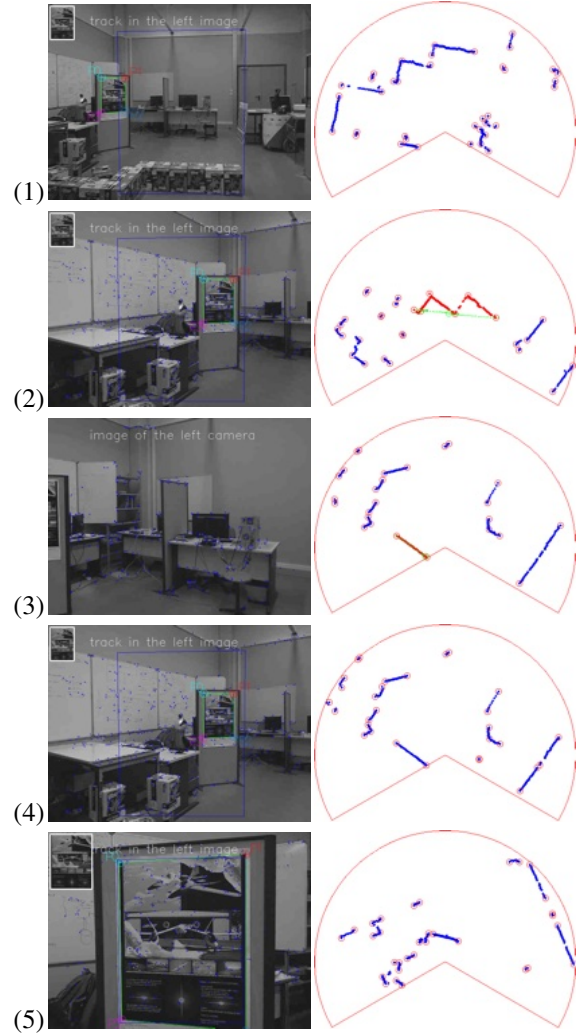


Fig. 6. Camera images (left) and laser data (right) at the five milestones. During target loss, projected points are predictions rather than visual measurements.

C. Qualitative analysis of the complete run

The sequence confirms the intended complementarity between the two proposed components. Before the blackout, the constrained estimator supplies the last geometrically consistent target model despite the increasing viewpoint change. During the bypass, the target projection moves beyond the image boundary, but the homography prediction remains defined because it is propagated in projective space rather than clipped to the camera frame. After clearance, only the predicted horizontal bearing is used to steer the robot, which limits the effect of corner-level prediction errors. Once the target re-enters the image, the two-point estimator can generate a new hypothesis from a small number of correct matches and measured IBVS is restarted.

The experiment also illustrates the distinct roles of prediction and feedback. Prediction bridges the interval in which no target measurement exists; it cannot correct odometric drift. Consequently, the method does not attempt to complete the final positioning task in open loop. Its purpose is to preserve enough directional information to recover the visual loop as soon as the target becomes observable again.

D. Evaluation protocol and limitations

The available archived material supports a qualitative demonstration of the complete navigation sequence and a direct visual comparison between the constrained and general RANSAC models, as illustrated in Fig. 2. It does not contain all raw time-synchronised logs required to reproduce precise values of clearance, angular jerk, or pixel-domain prediction drift. Such reconstructed numerical values are therefore not reported in this paper.

For a fully quantitative submission, the following measurements should be computed directly from the archived correspondences and ego-motion logs: (i) RANSAC success rate, transfer error, iteration count, and computation time as functions of the injected outlier ratio; (ii) target-centroid and corner prediction errors as functions of blackout duration; and (iii) re-acquisition time and success rate over repeated runs. The relevant prediction error for M reference points is

$$e_H(k) = \frac{1}{M} \sum_{i=1}^M \left\| \pi \left(\hat{\mathbf{H}}_k \mathbf{x}_i^r \right) - \mathbf{x}_i^{\text{gt}}(k) \right\|_2, \quad (13)$$

where $\pi(\cdot)$ denotes homogeneous normalisation. Ground truth may be obtained by manual corner annotation in frames where the target is visible or by an external pose-measurement system.

The method also relies on explicit assumptions: the target is planar and approximately vertical, robot roll and pitch remain small, and the translation scale is locally constant during the loss interval. Violation of these assumptions introduces structured model error. A useful validation should therefore include controlled perturbations of target tilt, camera roll/pitch, and odometric scale. Such tests would identify the operating range in which the constrained solver remains preferable to an unconstrained model and the range in which switching to a general homography becomes necessary. Nevertheless, the present experiment shows that the predicted target bearing remains useful for re-acquisition after a prolonged visual blackout.

E. Computational considerations

Both proposed modules are compatible with real-time implementation. The minimal solver requires the singular-value decomposition of a 4×5 matrix for each hypothesis, while model scoring is linear in the number of putative matches. Compared with four-point RANSAC, the main gain is not the cost of one hypothesis but the lower number of hypotheses required at a given outlier ratio. During complete loss, the prediction requires only the composition of a rotation with a rank-one translation-plane term. The re-acquisition command then uses the predicted centroid and does not require an image-wide search at every control cycle. In practice, the most expensive operations remain feature extraction and matching, which are common to both the constrained and general estimators.

VII. CONCLUSION

This paper presented a constrained homography estimator and a geometric target-recovery method for vision-based

navigation of a ground mobile robot. Planar camera motion and a vertical target reduce the homography to four effective degrees of freedom, enabling a two-correspondence RANSAC solver. When all visual features disappear, the last valid plane estimate is combined with accumulated ego-motion to predict the current homography. The formulation removes an unknown but locally constant translation scale and supplies a target bearing for active re-acquisition. A real indoor navigation sequence demonstrated obstacle bypass, a visual blackout longer than ten seconds, target re-acquisition, and resumption of measured IBVS. Future work will quantify robustness over repeated trials and relax the vertical-plane, planar-motion, and constant-scale assumptions.

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