A Model to Image Straight Line Matching Method for Vision-Based Indoor Mobile Robot Self-Location

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Abstract

An efficient and simple method for matching image features to a model is presented. It is designed to indoor mobile robot self-location. It is a two stage method based on interpretation tree search approach and using straight line correspondences. In the first stage a set of matching hypothesis is generated. Exploiting the specificity of the mobile robotics context, the global interpretation tree is divided into two sub-trees and then two geometric constraints are defined directly on 2D-3D correspondences in order to improve pruning and search efficiency. In the second stage, the pose is calculated for each matching hypothesis and the best one is selected according to a defined error function. Test results illustrate the performances of the approach.

Key words: *Model-Based Localisation, Vision-Based Localisation, Object Recognition, Feature Matching*

1. Introduction

A mobile robot needs to have an exact knowledge of its position in its environment to execute some classical tasks such as trajectory planning or autonomous navigation. Researchers have developed a variety of techniques for mobile robot positioning. Solutions can be categorised into two groups: relative localisation (also called dead-reckoning) and absolute localisation. Algorithms using dead-reckoning are simple and fast. However, some factors as slippage make the error accumulate and location uncertainty increase. Dead reckoning is then not sufficient. Methods based on absolute localisation principle are more complex and costly in computation time [1]. One solution is to combine two methods (one from each group).

Vision-based localisation using landmarks is a very studied absolute localisation technique [1,2,3,4,5]. When these landmarks belong to a stored representation of the environment (model) we talk about *model-based localisation*. Geometric shapes such as points, lines or curves are usually used as landmarks. Their position must be fixed and known. Approaches using natural landmarks (without modification of the environment) are highly desirable. However, extraction of this type of features in a scene is not straightforward and their recognition is more complex.

The classical approach for the camera pose recovery follows four stages: image acquisition from the current robot position, image segmentation and feature extraction, matching between 2D-image and 3D-model features, and camera pose computation.

One of the most important aspects of model-based localisation is matching, i.e. the determination of the correct correspondence between image features and model-features. Most of the methods treating this problem were developed for the domain of object recognition [6,7,8,9,10,11,12,13,14,15]. In mobile robotics, the problem is equivalent if considering local parts of the model of the indoor environment as objects to recognise. However, some particularities have to be taken into account. For example the dimension of the objects to recognise is great in comparison to their distance to the camera. Thus, the use of a full perspective camera model rather than simplified models is essential.

Matching methods can be classified in two groups: methods which search a solution in the “correspondence space” such as alignment [7,8], geometric hashing [9] or interpretation tree search [11,12] and those which search in the “transformation space” such as generalised Hough transform[10]. One of the most popular approaches is the interpretation tree search introduced by Grimson [11,12]. For two sets of model features and image features all the combinations of their elements are ordered in a tree. Each node of the tree represents correspondence between one model and one image feature. Paths of branches from the root relating nodes represent correspondence combinations. The basic algorithm is to search a path consistent with the observed scene and to validate it by computing a pose using its set of correspondences. Geometric constraints are incorporated to the search to prune the tree. The number of paths increases exponentially with respect to the number of model and image features. Algorithm efficiency is highly correlated to capacity of geometric constraints to prune large parts of the global tree. Geometric constraints concern correspondences of features expressed in the same number of dimension spaces (2D image feature with 2D model feature or 3D features estimated by stereo-vision with 3D model features).

In this paper, a two stage method for mobile robot localisation based on a tree search approach and using straight line correspondences is presented. The first stage serves to select a small set of matching hypothesis. Indeed, exploiting some particularities of the context, the sets of image lines and model segments are both divided into two subsets. Two smaller interpretation trees are then obtained. Two different geometric constraints which can be applied directly on 2D-3D correspondences are derived and used to prune the interpretation trees. In the second stage, poses corresponding to retained matching hypothesis are calculated. An error function is used to select the optimal match if it does exist. In section 2, the problematic and the basic approach of vision based localisation are reminded and then, The mathematical formulation of the problem and the details of each stage of our method are presented. Section 3 contains test results and comments on method performances with synthetic images.

2. Matching 2D image lines to 3D model segments

Our method uses straight line correspondences. Existing methods for camera pose computation uses generally point or straight line correspondences [16,17,18]. Image features result from image segmentation into contours. Contours correspond to physical elements in the indoor work space, such as edges constituted by intersections between surfaces of the flat. These edges tend to be straight segments. Lines are easier to extract from contour images and their characterisation by polygonal approximation is reliable even in the presence of noise. Partial occlusion (due to the view angle or the presence of non-modelled objects) does not affect line representation parameters. Then, it seems more prudent to use straight line correspondences. Thus, the 3D model can simply comprise a set of straight segments.

In this section we focus on the problem of finding the correct matching between the set of image lines and model lines. The most popular method is the interpretation tree search method using point correspondences presented by Grimson [11,12]. Murray [15] developed a variant using line correspondences. Considering a set of m model segments $\mathbf{L}=\{L_1,L_2,\ldots,L_m\}$ and a set of n image lines $\mathbf{l}=\{l_1,l_2,\ldots,l_n\}$, the interpretation tree represents all the possible combinations of couples of **L** and **l** elements. The theoretical number of possibilities (taking into account that one or more model line may not be present in the image due to occlusion or non-detection by contour extraction) is $(n+1)^m$. But a great part of the tree is never examined. Indeed, some geometric constraints are used to prune the tree. The most used constraints are unary and binary constraints. Unary constraints have to be satisfied by each couple L_i-l_j such as length. Binary constraints specifies that for each set of two couples L_i-l_j, L_k-l_l satisfying the unary constraint, the angle between L_i and L_k must be the same as the estimated angle between l_j and l_l. Higher order geometric constraints can be introduced. One weakness of the approach is that the two sets **L** and **l** have to be expressed in the same number of dimension space. Model segments are in a 3D space since image lines are in a 2D space. One have then to estimate the 3D representation of each 2D image line by stereovision technique. Another eventuality is to introduce in the search process a verification step by computing the camera pose from the current hypothetical matching. In projecting each model line on the image using the computed pose and comparing obtained lines with viewed lines, one can accept or reject the current matching. Unfortunately, this increases dramatically the computation cost and makes the algorithm unusable in a real application.

Our aim is to develop a well adapted matching method to mobile robotics context by improving efficiency and computational cost of the search process. Three factors must be taken into account: *i.* the number of possible combinations have to be reduced, *ii.* the classical geometric constraints must be usable for 2D-3D correspondences, *iii.* the number of pose computing operations must be reduced to the minimum. We propose a two stage method working in the correspondence space exploiting the specificity of the context. The first stage serves to generate a finite and reduced set of correspondence hypothesis among the interpretation tree combinations. The approximate knowledge of the camera pose is used to select a subset of model segments which can be viewed from the assumed range of poses. Two geometric constraints are then used to discard non-consistent correspondences. In the second stage the retained matching hypothesis are ordered according to an error defined in the sum of squared error sense is calculated after pose recovery. The best combination is then selected as the desired camera location. Details of the two stages are presented in the following subsections after a mathematical formulation of the localisation problem.

2-1. Mathematical formulation of the localisation problem

To formalise the camera localisation problem, let us consider two co-ordinate systems; the world co-ordinate system $(o,\boldsymbol{x},\boldsymbol{y},\boldsymbol{z})$ related to the environment and the camera co-ordinate system $(o_c,\boldsymbol{x_c},\boldsymbol{y_c},\boldsymbol{z_c})$ where o_c is the camera optical centre and the image plane is orthogonal to $\boldsymbol{z_c}$ and situated at a distance f (focal lens) from o_c. Camera location is characterised by a translation vector $\mathbf{T} = [x\ y\ z]$ and a rotational matrix **R**. **T** represents the translation between o_c and o. **R** is composed of the three Euler angles Ψ, θ and ϕ about the $\boldsymbol{x_c}$, $\boldsymbol{y_c}$ and $\boldsymbol{z_c}$-axes. **R** and **T** carry the camera frame onto the world frame. In general, indoor mobile robots operate in a 3D environment, yet their displacements are in a 2D-space. Thus, the camera moves in an horizontal plane at a known and constant height. t_z and θ are then assumed to be known and Ψ is zero. The system then becomes a 3 DOF (degrees of freedom) one with parameters ϕ, x, y.

2-2. Matching hypothesis generation

Selecting model segments. A starting assumption necessary for the following method is that the robot has an approximate estimation of its location. This assumption is not very restricting. Indeed, most of mobile robots are equipped with wheel encoders which provide an estimation of the pose. In addition, a relatively large interval of poses is needed to start the matching process.
The complete model of the indoor work space contains generally a great number of segments. The *xy*-plane of possible positions is clustered into non-overlapping polygons called Edges Visibility Regions (EVR) by Talluri [3] or View Invariant Regions (VIR) by Simsarian [19]. A subset of segments of the global model is associated to each region. This subset contains the list of the segments visible from the corresponding region. Having an estimation of the camera orientation ϕ_e and position [x_e, y_e] and a higher bounds $\delta\phi$, δt of orientation and position estimation error, only few regions can be retained. Thus only segments belonging to the visibility lists of these regions will compose the set **L** of model segments participating to the matching process.
Unary geometric constraint definition. Let us consider a 3D line segment L_i of **L** defined by its direction vector $\mathbf{v}_i$ and its position vector $\mathbf{p}_i$ in the world co-ordinate system. $\mathbf{v}'_i=\mathbf{R}\mathbf{v}_i$ and $\mathbf{p}'_i=\mathbf{R}\mathbf{p}_i+\mathbf{T}$ are the expressions of $\mathbf{v}_i$ and $\mathbf{p}_i$ in the camera co-ordinate system. Assuming that l_i is the projection of L_i in the image plane, L_i and l_i belongs to an interpretation plane passing through the focus point o_c. Let $\mathbf{n}_i$ be the unit vector normal to this plane expressed in the camera co-ordinates system (Figure 1). It is possible to calculate $\mathbf{n}_i$ knowing l_i and the intrinsic camera parameters u_0, v_0, α_u, α_v [17]. Expressing the dot products $\mathbf{v}'_i\,.\mathbf{n}_i$ and $\mathbf{p}'_i.\mathbf{n}_i$, one can write

$$\mathbf{n}_i.\mathbf{R}.\mathbf{v}_i = 0$$
$$\mathbf{n}_i.(\mathbf{R}.\mathbf{p}_i + \mathbf{T}) = 0$$

According to the mobile robotic context presented before, the rotation matrix can be written as follows

$$\mathbf{R} = \begin{pmatrix} \cos(\theta)\cos(\phi) & -\cos(\theta)\sin(\phi) & \sin(\theta) \\ \sin(\phi) & \cos(\phi) & 0 \\ -\sin(\theta)\cos(\phi) & -\sin(\theta)\sin(\phi) & \cos(\theta) \end{pmatrix}$$

By replacing **R** we obtain two equations of the following forms:

$$a_i.\cos(\phi) + b_i.\sin(\phi) + c_i = 0$$
$$a'_i.x + b'_i.y + c'_i = 0$$

Thus, each correspondence permits to calculate ϕ and to constrain the position of the robot to belong to a straight line in the *xy*-plane whose equation is $a'_i.x + b'_i.y + c'_i = 0$.

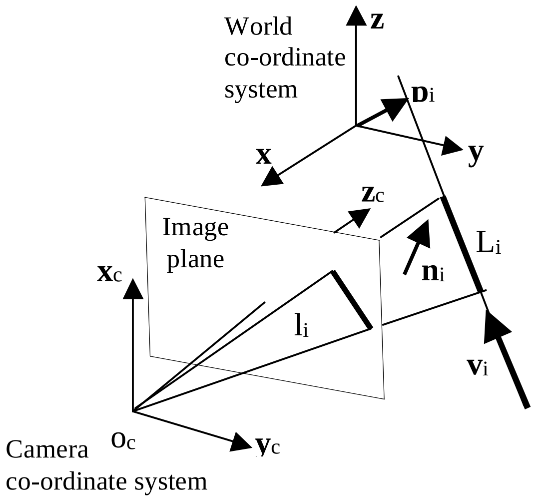

***Figure 1:** projection of a model segment*

A unary geometric constraint is then expressed as follows: a correspondence L_i-l_j is an acceptable matching if the corresponding calculated orientation verifies $|\phi-\phi_e|<\delta\phi$ and the calculated straight line intersects with the circle whose centre is [x_e,y_e] and whose ray is δt (figure 2).

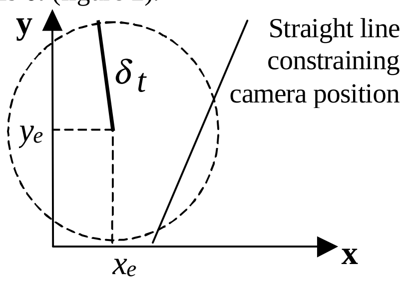

***Figure 2:** unary geometric constraint*

Unfortunately, if the model segment is vertical, parameters a_i and b_i are zero. The orientation can not be calculated in this way. Unary geometric constraint is then unusable. We propose the following solution.

Binary geometric constraint definition. Betke [5] uses vertical lines to calculate the camera pose. She assumes that θ=90°. Thus, the projection of a vertical segment of the model is a vertical line in the image. In practise, in most mobile robots θ is known but variable. The projection of a vertical segment is then not necessarily vertical in the image. The previous method can not be used. We propose to extend the method to the case where $\theta\neq$ 90°. The solution is first presented for θ = 90° and then extended to the general case.
Let us consider a subset of vertical segments $\mathbf{L_v}$ of **L** and a subset of vertical image lines $\mathbf{l_v}$ of **l**. The equation of l_{vi} in the image plane can be written $v=v_i$.

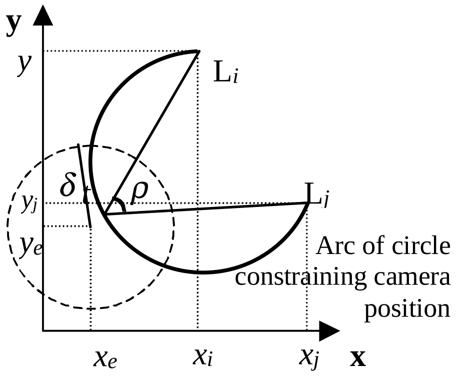

Figure 3: *binary geometric constraint (top view of two vertical model segments L_i and L_j)*

Considering a couple of correspondences (L_i-l_k,L_j-l_l), the angle of view ρ between L_i and L_j can be calculated from the image measurements v_k, v_l and the camera intrinsic parameters. This angle restricts the possible camera position to an arc of a circle as shown in figure 3. Theoretically, two circles can verify the angular constraint. The false one can be eliminated by verifying if the right to left order of the vertical lines in the image is consistent with each range of positions.

Then, a binary geometric constraints can be expressed as follows : a couple of correspondences (L_i-l_k,L_j-l_l) is acceptable if the corresponding circle arc intersects with the circle whose centre is [x_e,y_e] and whose ray is δt and the right to left image order of l_k and l_l is preserved.

To generalise the binary constraint to the case where θ is not equal to 90°, one have first to identify the image lines which potentially correspond to vertical segments in the model. An image line l is defined in the image plane by its slope ρ and its distance to the origin d. l may correspond to a vertical segment in the model if some rules are verified:

- l does not intersect the middle vertical line of the image plane;
- if $0<\theta < 90°$ then
  $\rho_{min}<\rho<\rho_{max}$ when l is contained in the image right half, $-\rho_{max}<\rho<-\rho_{min}$ otherwise.
- if $90°<\theta < 180°$ then
  $-\rho_{max}<\rho<-\rho_{min}$ when l is contained in the image right half, $\rho_{min}<\rho<\rho_{max}$ otherwise.

ρ_{min} and ρ_{max} are proportional to θ_{min} and θ_{max} which generally can be situated around 45° and 135° respectively (figure 4).

The limits imposed by these rules must be made fuzzy in introducing flexible thresholds to take into account noisy data such as line parameters estimation and camera calibration errors.

We have now a set of image lines which can possibly correspond to vertical edges. To apply the binary constraint we need to calculate the v_i measurements. If the camera was in an horizontal position (θ=90°) the lines would be vertical and have as equation $v=v_i$. We define a so called “horizon” line in the image whose equation is $u=u_{h0}$. u_{h0} can easily be calculated knowing θ. We demonstrate in appendix A that v_i can be obtained from the intersections v_{hi} of each line with the horizon line (figure 4) as follows $v_i = (v_{hi} - v_0).\sin(\theta) + v_0$.

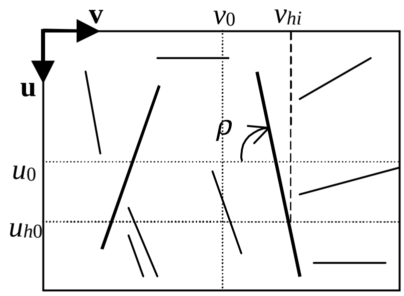

Figure 4: *Only lines in bold are selected as possibly corresponding to vertical edges.*

Summary. The matching hypothesis generation process can now be summarised as follows:

- Starting from a set of m model lines $\mathbf{L}=\{L_1,L_2,\ldots,L_m\}$ and a set of n image lines $\mathbf{l}=\{l_1,l_2,\ldots,l_n\}$, **L** is first divided into two groups of vertical segments $\mathbf{L_v}=\{L_1,L_2,\ldots,L_{mv}\}$ and non-vertical segments $\mathbf{L_h}=\{L_1,L_2,\ldots,L_{mh}\}$. A subset $\mathbf{l_v}$ is extracted from **l** using the previous procedure.
- The unary constraint is applied on the lines of $\mathbf{L_h}$ and **l**. Only retained correspondences serve to compose a list of combinations of $\mathbf{L_h}$ and **l** elements. The binary constraint is applied on the couples of correspondences formed from $\mathbf{L_v}$ and $\mathbf{l_v}$. Only retained couples serve to compose a list of combinations of $\mathbf{L_h}$ and **l** elements.
- The obtained two lists are then combined to form a complete list of possible matching hypothesis of **L** and **l** elements.

2-3. Matching Hypothesis verification

The thresholds used in unary and binary constraints are not tight enough to eliminate all the false matching hypothesis. The last step is to select the optimal match, if it does exist, among the set of retained hypothesis. Several approaches exist taking into account the fraction of correctly matched model features, the probability of accidental pairings and image reconstruction errors [8,13,20].

Our approach is to select the best matching hypothesis. For each matching hypothesis, a camera pose is computed by mean of least square method [17,18]. The error between projections of model segments using the calculated pose and viewed lines is estimated. In the theoretical case, the right matching hypothesis would produce null errors. In practise, image measurements contains noise introduced at different stages (image acquisition, segmentation into contours, polygonal approximation). In addition, calibration errors make the projection of model segments uncertain. Thus, hypothesis are ranked according to a score calculated on the basis of the director vectors of model segments and observed normal vectors of image lines as follows:

$$E = \frac{1}{N^2}\sum_{i=1}^{N}(\mathbf{n}_i^t \mathbf{R}\mathbf{v}_i)^2 + \frac{1}{N^2}\sum_{i=1}^{N}(\mathbf{n}_i^t(\mathbf{R}\mathbf{v}_i + \mathbf{T}))^2$$

where N is the number of matched lines.
If all the hypothesis have a score greater than a threshold determined empirically [20], no hypothesis is accepted.

2-4. discussion

A fundamental problem in matching methods based on tree search is dimensions of the correspondence space. In the presented method, the introduction of a constraint on the image lines permits to divide the tree into two sub-trees. This, in fact, can be seen as a large pruning of the initial tree because it eliminates, before starting the search, a great number of correspondence possibilities and reduces the probability of accidental matching.
Another difficulty encountered by model-based object recognition algorithms is the existence of a minimum number of correctly matched features which permits to decide whether an object is recognised on the image. The extension of the binary constraint to the general case ($\theta \neq 90°$) makes possible the use of vertical segments and then potentially increases the number of correspondences. The decision is then more reliable.
Finally, both unary and binary geometric constraints concerns directly 2D to 3D matching. It is thus not necessary to introduce pose recovery operations in the hypothesis generation stage or to use stereo sensors to express image measurements in a 3-dimension space.
When the system is completely “lost”, the robot must be stopped and the time constraint becomes more supple. The System can then repeat the matching process with different starting pose estimations (one for each VIR) until it finds a consistent pose.

3. Test of the method

The presented method has been tested on synthetic images. The goal of the test with synthetic data is to make a statistic study of method performances in various useful situations. The camera simulator specifications were: resolution=640x480, u_0=240, v_0=320, α_u=-900 and α_v=900. First a model of a flat room was built. 100 camera reference pose samples were randomly generated. An image of the model was simulated for each pose. The number of seen segments varied from 5 to 9. The method was applied to compute the best model segment to image line correspondences.
Uncertainty introduced by imaging process and line extraction program was simulated by adding uniformly distributed noise on the synthetic image line parameters ρ, d and $\mathbf{n}$. Randomly generated lines were added to the synthetic image to simulate the presence of non-modelled objects in the scene. Initial pose estimations necessary to the algorithm were generated randomly. A pose estimation quality (PEQ), parameter, determining the difference between reference pose and estimated pose, was defined (table 1).

PEQ	*1*	*2*	*3*	*4*	*5*
δt (m)	0.2	0.4	0.6	0.8	1.0
$\delta\phi$ (°)	10	20	30	40	50

Table 1: *values of PEQ used in the tests*

The first results concerns performances of the matching hypothesis generation stage. Figure 5 shows the number of possible combinations retained after applying the first stage. Even with non accurate pose estimation (PEQ=5), the number of retained combinations is not important (less than 25). This provides good conditions and improve efficiency of the next stage.
Performances of hypothesis verification stage are related to the values of E. A least square method was used to compute the camera pose for each retained hypothesis. Results are presented in figure 6. Graphs represent mean value and standard deviation of the 5 smaller values of E. The smaller value corresponded in all the cases to the correct match. E can be then considered as a reliable criterion for selecting the correct matching hypothesis. In addition, the sensitive increasing of E for the false hypothesis permits to choose a threshold value to avoid acceptance of false solutions. In this test the threshold can be situated around 0.002.

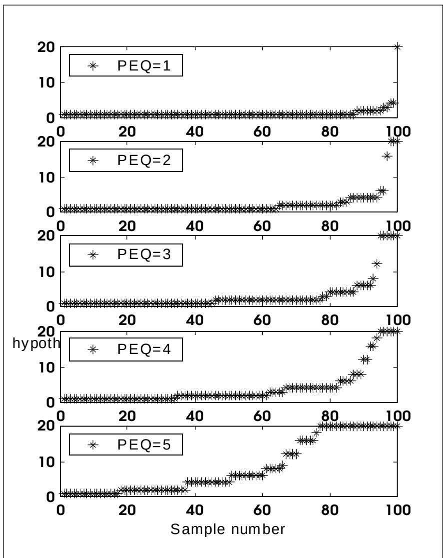

Figure 5: *number of hypothesis after the 1st stage*

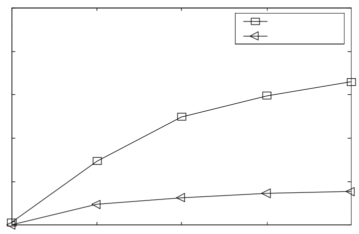

Figure 6: *mean value and standard deviation of E.*

4. Conclusions and future works

A method for matching 2D image straight lines to 3D model segments was presented. It was developed for mobile robot self-location and takes into account specificities of this context such as the number of degrees of freedom and the possibility of having an estimate of the current pose. The main contributions of this work are the restriction of the space of correspondences induced by subdivision of the sets of model and image features and the using of 2D-3D constraints which permit to reduce the number of pose calculating operations. Simulation results show that the objectives were reached with test conditions close to those of a real application in term of noise in image data or presence of non modelled objects.

To make the method completely based on vision, methods for calculating the initial pose estimation have to be developed. This is the interest of our future works.

Appendix A

Let l_i be an image line verifying the constraints of section 2.2 viewed with a camera orientation $\mathbf{R}(\phi, \theta, 0)$ and translation $\mathbf{T}[x\ y\ z]^t$. v_{hi} is the co-ordinate of its intersection with the horizon line. This intersection point is the projection of a point $\mathbf{p}_i(x_i, y_i, z_i)$ on the corresponding model segment. In projecting $\mathbf{p}_i$ we have

Since z_i=z we obtain

The goal is to calculate v_i if θ was equal to 90°.

Thus $v_i = (v_{hi} - v_0) \cdot \sin(\theta) + v_0$

5. References

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