Appearance-Based SLAM for Mobile Robots

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Abstract. This paper reviews new challenges in the area of long-term navigation, and new approaches to environment representation and robots capable of coping with dynamic environments. As a result of this review, we propose an appearance-based simultaneous localization and mapping (SLAM) solution which represents the robot environment using an appearance-based topological map. Dynamic environment changes are dealt with using human memory and fixed action pattern concepts. The former is used to build a histogram to register local feature stability, the latter for robot navigation purposes. We take omnidirectional vision and laser range data to extract textured 2D scans as global features, and textured-vertical edges as local features for map updating and robot localization. From the navigational point of view, we consider visual potential field-based behavior to adjust high level motion commands.

Keywords. Mapping, localization, computer vision.

Introduction

The simultaneous localization and mapping (SLAM) problem has been under investigation for two decades. Excellent surveys have been written to keep SLAM solutions on-track [1]. Our state-of-the-art review, we have grouped the SLAM methods found into: a) simultaneous mapping and localization processes (on-line) [2]-[13], and b) those with an off-line map learning phase [14]-[21]. SLAM approaches can be both geometric and non-geometric, and the latter includes topological maps that, merged with geometric information, provide human-readable information about the environment. Nowadays, SLAM solutions are combined with high-level environment representations such as dense 3D models [9], image qualitative descriptions [3] and appearance-based representations. These last represent the environment as a whole, not just by using local features (i.e., points or corners), which can easily change or disappear, but by using high-level image features with similarity measures for localization and place recognition purposes. These environment models are widely used in service robots [9], robots for disabled people [8], and autonomous underwater vehicles for structure inspection [22]. In general, the latest trends have focused on merging geometric information for specific robot navigation issues, and appearance-based information for human-robot interaction.

We propose an appearance-based SLAM solution with two main contributions. The first is our implementation of human memory models [23] to deal with dynamic environment mapping and long-term navigation. This concept has been used from mobile robot programming architectures [24] until environment models [13]. In this

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model short-term memory (STM) and long-term memory (LTM) interact to update, actively forget or reinforce past observations. Our approach, in contrast to [13], builds a histogram which stores stability values about local features and increases (if feature is detected) or decreases (if the feature is no longer available) the local feature bin value. The second contribution is an adaptation of a human behavioral concept called fixed action patterns (FAP) [25], which allows, in a robotics context, the implementation of well-defined or optimal motion controllers, but with a final command that is adjusted by sensory inputs to deal with dynamic changes in the environment. Using these concepts, we propose an appearance-based topological map building technique, in which each node stores short- and long-term features, their localization data, the environment appearance, and a parameterized robot-heading controller. In contrast to other approaches, we believe our proposal is able to cope with changing environments and long-term mapping and navigation, and in addition marks a step forward in semantic environment representation [21], [26].

The remainder of this paper is organized as follows: Section 1 describes the state-of-the-art, Section 2 presents our proposal, and Section 3 contains our conclusion.

1. Related Work

Table 1 shows our SLAM solutions review. The list has been classified, from left to right, by the simultaneousness of the mapping and localization process, the SLAM approach used, the similarity or matching method employed to modify the robot map, and the environment-type of each reference. It can be seen that the simultaneousness of the mapping and localization process is a very challenging task [2]-[13]. Even though appearance-based solutions are usually implemented in two-phase procedures – map learning and navigation [14]-[21] – this task division is not always possible in real environments, since appearance-based models often define untraceable image similarity conditions to build semantic maps [21], dense 3D representations [9], or environmental models with graph clustering properties [19]. SLAM approaches with appearance-based environment representation involve probabilistic [11], [12], hybrid topological-metric [10], particle filter [5], [6], machine learning [20] and native appearance-based approaches [7], [8]. However, they do not focus on dealing with dynamic environments due to the simultaneousness of their mapping and localization process and the complexity of the environmental features. Besides this, their environment representation is not suitable for either long-term navigation or representations exploiting details of the environmental structure, except in works such as [8], [13].

The strength of appearance-based models lies in their ability to represent the environment through high-level image features, using similarity measures to decide if new information can be added to the robot map, which can often limit the Real-Time processing [7]. Table 1 also shows the most common approaches in environment description, such as color histograms, multidimensional histograms [16], SIFT and SURF descriptors [3], [17], eigen-images [15] and specialized descriptors like PHLAC [6]. One aspect is highlighted: the features and their descriptors do not exploit either details of the environment structure or natural sensor information representation, for example, works which consider omnidirectional vision [11][16]-[19]. Another important aspect is the robot environment, which defines the application's scope and different kinds of challenges, such as occlusions, partial landmark knowledge, moving landmarks, unsuitable environment landmarks, illumination changes, and pedestrians [27], [28].

Appearance-based SLAM solutions often use rich sensorial information. Sensors commonly employed are monocular, binocular, and omnidirectional vision, laser range finders, or a combination of these. Omnidirectional vision is receiving special attention nowadays due its long-term landmark tracking, one-shot environment sense regardless of heading, reduced perceptual aliasing, robust to occlusions, can be fused with range data, and is less sensitive to noise [12], [15]. Such advantages outweigh its disadvantages, such as: not constant vertical/horizontal resolution, low image resolution and mirror distortions [15].

Table 1. SLAM solutions review

Ref.	Process	Approach	Similarity/Matching Method	Environment
[2]	On-line	Traditional SLAM	SP-model features	Indoor
[3]	On-line	Traditional SLAM	SIFT descriptors and cosine distance	Outdoor
[4]	On-line	Traditional SLAM	Object saliency score and ICP	Both
[5]	On-line	Rao-Blackwellized particle filter	SIFT, fastSLAM,	Indoor
[6]	On-line	Rao-Blackwellized particle filter	Polar high-order local auto-correlat	Indoor
[7]	On-line	Appearance-based top. SLAM	SIFT descriptors,L2 distance.	Both
[8]	On-line	Appearance-based top. SLAM	Quad-tree Appearance-based content	Indoor
[9]	On-line	Appearance-based top. SLAM	Vert. edges, DCT, Mahalanobis dist.	Both
[10]	On-line	Hybrid topological metric SLAM	Sensed Space Overlap sim. func.	Indoor
[11]	On-line	Prob. appearance-based SLAM	Features with DCT	Indoor
[12]	On-line	Prob. appearance-based SLAM	Fourier transf. and mix. of Gaussians	Indoor
[13]	On-line	Adaptive appearance-based SLAM	SURF features and nearest neighbor	Outdoor
[14]	Off-line	Appearance-base top. map. / nav.	Homographies	Indoor
[15]	Off-line	Appearance-base top. map. / nav.	Eigenspaces, PCA, Hausdorff Fract	Indoor
[16]	Off-line	Appearance-base top.map. / nav.	Color histograms and L2 distance	Indoor
[17]	Off-line	Appearance-base top.mapping	SIFT features, RANSAC estimator	Indoor
[18]	Off-line	Hybrid top. metric map	Machine learning approach	Indoor
[19]	Off-line	Hybrid appearance-based SLAM	SIFT features and L2 distance	Indoor
[20]	Off-line	Semantic mapping	Machine learning approach	Outdoor
[21]	Off-line	Semantic mapping	ICP based and kd-tree	Both

2. System Description

With the above state-of-the-art in mind, our system proposal basically consists of four modules: perception, image analysis, mapping and localization, and robot navigation (see Figure 1). The perceptual module receives the 2D raw range data and the omnidirectional images, which are fused once a calibration procedure of both sensors has been performed. The image analysis module extracts 2D scan landmarks and local vertical edge features as soon as an image is available, and its corresponding textured planes, feature descriptors and similarity measures are calculated. These data are used to build a robot localization hypothesis, which is afterwards reinforced through the SLAM method used [29]. In this module the node's appearance is initialized. At the mapping module, the system updates the map information in accordance with our interpretation of STM, LTM and FAP concepts. The last module is navigation, where a behavior programming approach is taken [30] with three main behaviors, listed in terms of priority from high to low as follows: a reactive visual potential field behavior to cope with dynamic environments; a mapping behavior for exploration tasks; and a FAP coordinator, which executes one of the heading controllers available. The arbitration of these three behaviors is performed through a cooperative coordinator.

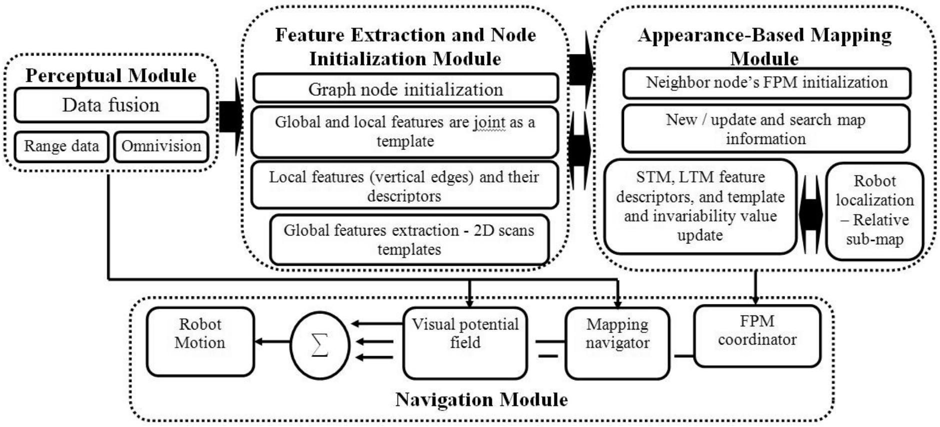

Figure 1. Process overview: perception, feature extraction, localization, mapping, and navigation modules.

The perceptual module task, where image and depth information are fused, is summarized in Figure 2. To carry out this task, a camera model and a laser model must be obtained. This can be done using some popular tools to calibrate these sensors such as [31] and [32]. Given a pixel *(u, v)* in the image plane, the orientation vector, as shown in Eq.(1), can then be recovered from the effective viewpoint to the 3D point [33].

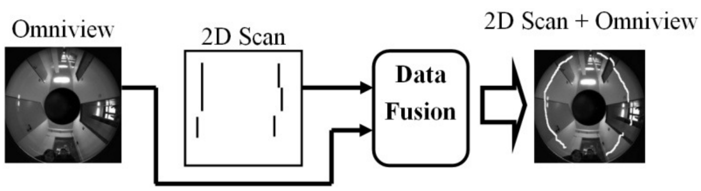

Figure 2. Omnidirectional and 2D range scan data fusion process.

$$\lambda X = \lambda[x \quad y \quad z]^T = T(u, v) \tag{1}$$

where λ is the depth factor; $X = [x \quad y \quad z]^T$ is the orientation vector; and T is the transformation matrix with intrinsic and extrinsic camera parameters. Some formulations of T are depicted in [34]. A 3D point λX can be re-projected on the image plane using Eq. (2).

$$[u \quad v]^T = T^{-1}(X) \tag{2}$$

It is assumed the camera coordinate system coincides with the effective viewpoint. In the same way as with the camera model, the laser scanner assumes a previous calibration. The laser and the omnidirectional camera are aligned along the Z axis of the camera mirror; but since this alignment is not exact, the corresponding offsets must be estimated through the calibration mentioned above. The extrinsic sensor model is shown in Eq. (3)

$$[x \quad y \quad z]^T = P_{INT}\begin{bmatrix} \cos(\theta_i) & -sin(\theta_i) & 0 & 0 \\ sin(\theta_i) & cos(\theta_i) & 0 & 0 \\ 0 & 0 & 1 & \mathrm{d_z} \\ 0 & 0 & 0 & 1 \end{bmatrix}[0\ \delta_i 0\ 1]^T \tag{3}$$

where, P_{INT} is the calibration sensor matrix followed by the extrinsic sensor model, which assumes a Y axis pointing forward and a Z axis pointing upwards; δ_i is the *i-th* range reading; θ_i is the orientation of the *i-th* measure; d_z is the distance between the camera effective viewpoint and the 2D scan center; and $[x \quad y \quad z]^T$ are the coordinates of each measured point relative to the system frame.

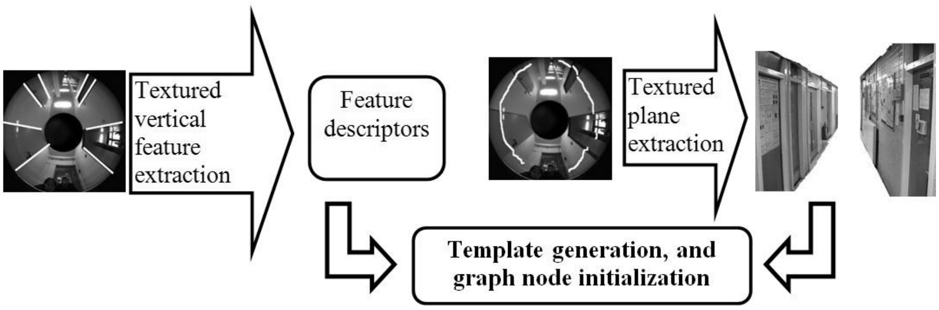

Figure 3. Description of plane extraction, vertical line features, their descriptors and scene interpretation.

Figure 3 shows an outline of the image analysis module, where three goals can be observed: global and local feature extraction, and node initialization. The first goal extracts 2D scans, which are joined to textured planes from the actual scene as global features. Given a cloud of observed 2D scan points P_o, we need to find out if P_o matches a stored P_t of 2D scan points. If P_o matches, local features are extracted and textured planes are built for localization and navigation proposes. If P_o does not match, node initialization is performed. In order to see if P_o and P_t match, the feature pose relative to the robot's z_o pose must be estimated as shown in Eq. (4) [32].

$$z_o = \begin{bmatrix} x_o \\ y_o \\ \theta_o \end{bmatrix} = \begin{bmatrix} (x_t - x_r)cos\theta_r + (y_t - y_r)sin\theta_r \\ -(x_t - x_r)sin\theta_r + (y_t - y_r)cos\theta_r \\ \theta_t - \theta_r \end{bmatrix} \tag{4}$$

where x_o, y_o and θ_o are the estimated 2D scan positions; x_t, y_t and θ_t are the stored 2D scan positions; and x_r, y_r and θ_r are the actual robot positions. z_o is an initial guess based on the middle point of the current 2D scan. The actual 2D scan and the z_o are used for alignment via an iterative closest point (ICP) algorithm [4], with P_t, and its covariance matrix estimation obtained using a *saliency score* measure [4]. If the *saliency score* of the 2D scan is larger than a given threshold, local features are used to refine the robot localization. Otherwise node initialization begins.

The second goal extracts the local features and their descriptors to define a similarity measure. When an image is taken, two sets of features are found: the current image feature set and the node feature set. First, their similarity must be defined using the Mahalanobis distance as shown in Eq. (5), with the number of corresponding features greater than a given threshold. A similarity score is then defined as shown in Eq. (6) [13].

$$d_{ij} = \sqrt{\sum_k \frac{(f_{ik} - f_{jk})^2}{\sigma_k^2}} \tag{5}$$

$$M_{pq} = \frac{S_{pq}}{N_p} \times 100 \tag{6}$$

where d_{ij} is the Mahalanobis distance between the i-th graph node and the actual image j; f_{ik} and f_{jk} are the corresponding features descriptors elements; σ_i is the node standard deviation; S_{pq} is the number of features between the images with a distance greater than a threshold; and N_p is the number of node features. This is a simple and fast way to estimate how close the actual image is to the node image, thereby helping the robot localization process. We consider vertical edges directly extracted from the omnidirectional image to be local features, so the extracting process is fast and the relative 3D position can be calculated by using the omnidirectional camera calibration parameters. Next, the vertical edges are used as an axis around which to build a small textured window, and then compute the local feature descriptors. To speed up the matching process, a kd-tree is built with the node's feature descriptors [8].

The third goal is graph node initialization, which is launched when the robot visits a new place. An appearance-based environment representation at the map node is then built using textured planes, the local feature descriptors are initialized as LTM descriptors, local features are mapped on the textured planes, and the similarity measures are added. The textured plane representation is built using the 2D scan with a *saliency score* higher than a given threshold [35]. The scene texture is obtained from the original image.

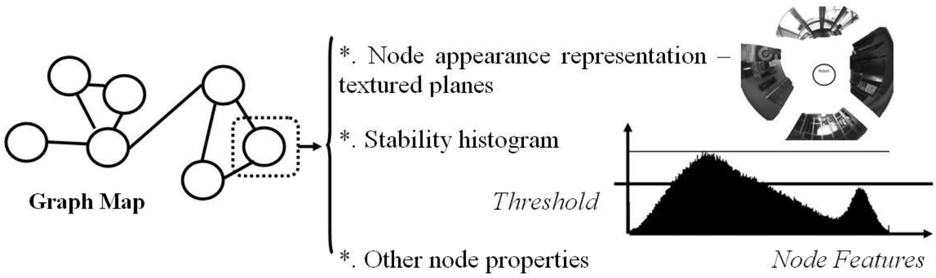

Figure 4. Appearance-based environment model and node content.

We consider topological maps since they are compact, consume less computer memory, can be stored in efficient data structures, and speed up the navigation process [1]. The appearance-based mapping module adds other node information: feature localization, the local feature stability histogram, and our FAP approach. Two main goals are shown in Figure 4: robot localization and map updating. Robot localization uses global and local similarity measures to search the topological map. The result is a hypothesis about the robot's position, which could be refined using Monte Carlo [6], Markov Models [1], particle filters [5], EKF, and Bayesian [28] approaches, but we prefer a relative submap method [29] since we want to avoid linearization issues arising from large pose uncertainties [27]. The motion model is given by the robot's kinematic constraints. The observation model is based on the similarity measure given by Eq. (6) and the epipolar geometry estimation for omnidirectional images of LTM node features [34]. Localization information and the histogram of local feature stability are then updated.

Map updating is requested once a new node is found, with the decision criteria being based on its similarity measure. The histogram values assigned to each feature descriptor are initialized in 1.0, and decrease if the feature descriptor is not present when the robot re-visits the place. Figure 4 shows the local feature stability histogram and a threshold, which shows whether the feature descriptor is an STM descriptor (values less than the threshold) or an LTM descriptor. The free navigation space, which is estimated using geometric robot constraints and the range data between the robot and obstacles around it, is valuable information to keep at each map node. This space is centered in the same submap frame used for robot localization [29]. Here, new graph connections are created to every other node if a similarity relationship exists. Our FAP concept approach adds a set of defined robot heading controllers between the actual node and linked ones, using the node position information and the robot's free space. The parameters of each heading controller include lineal and rotational robot velocities in order to assure safe, smooth movement and reference heading.

A robot's environment can change dynamically, and safe movement must be guaranteed in most cases. Common methods used are occupancy grid-based navigation [1], motion planning [8], behavioral approaches [30], and potential field [1]. We take a behavioral approach using potential field-based methods, since we need fast responses in dynamic environments, and to avoid grid resolution and high dimensional work-space problems. With regard to the navigation module, we consider two states: when the robot does not have a map, and when it has one.

As a special case, there is a third state for dynamic change of environment occurring when the robot is in one of the two states above. This module takes a behavioral programming approach [30], in which three behaviors are cited from high to low priority as follows: a potential visual field, mapping, and FAP coordinator behavior. This last behavior is activated when the robot has a map; each time it achieves a node, it executes the associated controller, so that other nodes or a goal position can be attractors in the navigation task. The mapping behavior is activated when the robot finds new nodes to add, thereby allowing exploration tasks based on the free space available. Finally, the potential visual field behavior is a fast obstacle avoidance approach, which uses the information given by the perceptual module to adjust mapping and FAP behavior according to the environment sensed.

3. Conclusion

A review of SLAM and appearance-based solutions has been presented with desirable characteristics such as new environment representations, long-term navigation, dealing with dynamic environments, suitable environment-dependent features, and fewer occlusion problems. As a result of this state-of-the-art analysis, we propose a novel approach for appearance-based SLAM based on human memory and behavioral concepts. We think the manner in which the STM, LTM and FAP concepts have been proposed will allow appearance-based map building, dealing with changing environments, and long-term navigation. The STM and LTM concepts will allow local feature stability to register in the environment through histograms, and local feature epipolar geometry will be calculated using features classified as LTM in order to ensure optimum localization and mapping results, and smooth movements. The histogram values can be interpreted as a probability density function, such that each value represents the local feature likelihood at each map node. Global and local features, according to environment structure details, are considered: textured planes can be extracted from 2D scans and omnidirectional vision, and textured vertical edges can be extracted directly from an omnidirectional image, with both taking advantage of man-made structures to represent environment appearance. The FAP concept is used at the navigation stage, where sudden obstacles are safely avoided by adjusting FAP behavior through a visual potential field. We believe this work is a step towards the semantic representation of environments, which will make it possible for computational intelligence approaches to be applied to robots' learning of places.

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