Survey: Visual Navigation for Mobile Robot

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ABSTRACT
There has been countless researches for vision based navigation and control in the field of autonomous mobile robot. Vision which was costlier in terms of processing power was not good enough for real time application in early days of robotics. But with new approaches, better computational power and effective algorithm, vision was area of interest for many researches for better navigation of robot which produced numerous research opportunities. For localization, automatic map construction, autonomous navigation, path following, inspection, monitoring or risky situation detection vision is most commonly used approach. This paper surveys almost all those papers by researchers whose works provided wide and numerous break-through in visual navigation techniques for land, aerial and autonomous underwater vehicles in the field of autonomous mobile robot.

Keywords
Mobile Robots, Visual Navigation

1. INTRODUCTION
Vision base navigation has been one of those few fields where countless researches have taken place in last two to three decade. Many algorithms and designs were produced which had better performances and which produced great breakthrough in this field. Apart from use of other sensors vision became more and more common in autonomous mobile robots which lead to new ideas and better scope for improvement in robot navigation.

Navigation can be defined as the process or activity of accurately ascertaining one's position and planning and following a route. Many varied sensors, both combined and individual has been used for this purpose which has led to wide researches providing many different solutions. Since vision was incorporated into mobile robotics, it has been a source of countless research contributions since it can increase the scope of application of autonomous mobile robots. The navigation algorithms which are having high performance are incorporated into the robot localization environment.

Conventional vision based navigation algorithms have been in used mostly for autonomous ground vehicles (AGV). But recent time the researchers finds its scope towards the unmanned aerial vehicles (UAV). The UAVs have a wide area of applications like search and rescue operations during natural calamities, surveillance, cinema shooting and many others. However the UAVs should demonstrate very high degree of awareness and correctness in order to execute obstacle avoidance and navigation process successfully. For underwater environments novel approach of sonar based systems are used. Presently autonomous underwater vehicles (AUV) are deployed in many real life scenarios like sea life monitoring, inspection of sunken anciental ships, defence missions, undersea installations inspection and maintenance etc.

No matter what type of vehicle is used for autonomous mobile robots, incorporation of visual sensor always guarantees the additional spectrum of flexibility which it can use for locomotion or controls. Now with the advent of Artificial Intelligence and its use in object detection and pattern recognition, navigation has geared and stepped up to new level of correctness and cohesiveness.

Patrolling is another area where robot navigation finds its application. Patrolling is the act navigation around a particular area in order to provide protection.Strategies need to be opted in order to cover the entire area with cost and time effective perspectives. This should have robust tracking system in order to cope up with occlusions and repeated patterns. Moreover this also must handle the illumination changes.

This paper proceeds with previous survey done by DeSouza et.al [14] 2002 and Bonin-Font et.al [19] 2008 and then proceeds to the new researches done beyond 2008.

2. FROM PRIMARY TECHNIQUES TO ADVANCE IN LATE 2000
De Souza and Kak partitioned robot navigation into two main subject's i.e. indoor and outdoor navigation. Indoor navigation was further divided into Map-Based navigation, Map-Building based navigation and Mapless navigation whereas outdoor navigation was divided into structured and unstructured environments.

In Map-Based navigation the robots were provided with the details of the environment depending on the research. Occupancy map was the first approach which used 2D projection of prominent features of and environment where robot had to navigate. Later on virtual force fields [6, 39] where every cell which was occupied by obstacle had repulsive force on a robot were used. Many authors assimilated uncertainties to account for sensor errors in occupancy maps. Table I below shows the most prominent visual navigation studies form 1987 till late 1990's.

Table 1. Prominent visual navigation studies till early 90s

Authors	Indoor/Outdoor	Category	Method
6, 39	Indoor	Map based	Force fields
8, 54	Indoor	Map based	Occupancy grids
9	Indoor	Map based	Occupancy grids
17, 66, 67	Indoor	Map based	Absolute localization
3	Indoor	Map based	Absolute localization
49	Indoor	Map based	Incremental

			localization
75	Indoor	Map based	Incremental localization
10	Indoor	Map based	Incremental localization
40,5, 50, 52, 55	Indoor	Map based	Topological map Incremental localization
37	Indoor	Map based	Landmark tracking
33	Indoor	Map based	Landmark tracking
52	Indoor	Map building	Stereo 3D reconstructio n
68	Indoor	Map building	Occupancy grid
7	Indoor	Map building	Occupancy grid
71	Indoor	Map building	Grid and topological representatio n
59	Indoor	Mapless	Optical flow
5	Indoor	Mapless	Optical flow
15	Indoor	Mapless	Optical flow
47	Indoor	Mapless	Appearance-based navigation
36	Indoor	Mapless	Appearance-based navigation
53	Indoor	Mapless	Appearance-based navigation
74	Outdoor	Structured environments	Road following
27-30	Outdoor	Structured environments	Road following
73	Outdoor	Structured environments	Road following
69, 70	Outdoor	Structured environments	Road following
35, 56	Outdoor	Structured environments	Road following
76	Outdoor	Unstructured environments	Random exploration
42	Outdoor	Unstructured environments	Given mission exploration
48	Outdoor	Unstructured environments	Random exploration

In Map-Building based navigation robots updates the maps about the environment as it perceives it using different sensors present in it. Moravec [52] was the first to explore this technique. Then Thorpe [68] refined the techniques used by Moravec. Thorpe extracted features from images and use it to generate their 3D coordinate. An occupancy grid of two square meter cells was used for representation of the features. Though better, these methods were not good enough for modelling the whole workspace as occupancy grid based strategies could be computationally inefficient for path planning and localization. Also sensor error creeps in as a factor for occupancy grid. Then came Thrun [71] who made remarkable contribution by combining best of occupancy grids and topological maps for navigation.

Now if a robot is place without any information about its environment; and if it starts navigating depending on perceived information, then this kind of system comes under Mapless navigation. Its movement depends in the features observed in its workspace. Prime techniques were optical-flow and appearance-based navigation. Techniques from Horn and Schunk [34] and Lucas and Kanade [44] were improvised for computation of optical flow. Santos-Victor et al [59] developed and interesting design by emulating Bee. The system proceeds forward with two cameras on each side perceiving the environment. Now if the flow on the both side is same then the system keeps proceeding forward. Change of flow in one side of the system produces the turning effect for navigation. But for this technique walls must be textured enough to compute optical flow. Matsumoto et al [47] and Jones et al [36] used templates for matching and navigating. They saved the sequence of images with which the robot compared the perceived images using correlation and then proceeded forward navigating the environment while Jones et al stored sequence of images and their associated actions which was used by robot to navigate in an environment. While navigating the robot recovered the template what best matched and if the match is above threshold the robot executes the related actions.

In structured environment, outdoor navigation refers to road following. It is the ability of the robot to detect the line of the road and then navigate accordingly. Tsugawa et al [74] pioneered on this technique in which pair of stereo camera was used to detect obstacle in automatic car driving approach. Thorpe [69, 70] with NAVLAB road following algorithm was one of the most outstanding in this approach. Other were VITS [73] road following framework equipped with obstacle detection and avoidance sub-system.

In unstructured environments where there are no regular properties that can be used for navigation, there are two possibilities i.e. the robot randomly explores the workspace. Wilcox’s et ta. Vehicle [76] is an example for this kind. Another possibility being the robot executes a mission with a goal position in which a map of the areas in which the robot moves has to be created and localization algorithm is also needed. RATLER by Krotkov and Herbert [42] in 1995 is an example for this kind.

From late 90s till 2008 techniques were matured and refined for better performance and effective systems. Bonin-Font et al distinguished between map-based and mapless navigation. Map based systems accounts almost all the techniques which build and/or use metric topological maps. The techniques which require certain information about the workspace are:

- Metric map-using navigation systems
- Metric map-building navigation systems and
- Topological map-based navigation systems

The system which needs complete information of the workspace before any navigation process starts falls under Metric map-using navigation system. If there is no available information about the environment then systems which falls under this category fails. The system which needs little or no information of the workspace but it starts to build the knowledge/ map through self-exploration falls under Metric map-building navigation systems. Map building and self-localization in navigation environment are assimilated into non-reactive systems. Basically in map-building it is assumed that localization can be done using some other techniques. In pure localization map of the environment is presumed to be available. Robots using map building approaches has to track their own position and orientation in its workspace continuously.

If exploration and mapping of a new workspace is to be done automatically and on the go then the robot must achieve these task:

- Safe exploration/navigation
- Mapping and
- Localization

SLAM (Simultaneous localization and mapping and CML (Concurrent mapping and localization) aims for strategies to explore, generate map and self-localize simultaneously in unknown workspace. Survey by Bonin-Font et al takes into account those techniques which use Visual Sensors for SLAM and CML.

Graph-based representation of the environment is known as topological map. These are simple and compact taking up less memory which in turn provides faster navigation process. These maps represent characteristic features of the environment which in turn can be associated with actions to be taken up. Robots' using this map falls under Topological Map-Based Navigation Systems.

Table 2 lists all the prominent researches till late 2000.

Table 2. Prominent metric map-using and building navigation systems from mid 90s till late 2000

Authors	SLAM/ CML	Category	Method
13	SLAM	Map building	Sequential mapping and localization
62, 63	SLAM	Map building	Landmarks localization and tracking
64, 65	SLAM	Map building	Landmarks extraction and occupancy grids
16, 24	SLAM	Map building	3D reconstruction using Stereo Trinocular vision system
12	SLAM	Map building	Map feature extraction
60	SLAM	Map building	Top-down Bayesian method based algorithm for landmark detection
45	SLAM	Map building	3D environment reconstruction using structure from motion(SFM)
72	SLAM	Map building	3D high density map and objection recognition
38, 58	SLAM	Map building	Human Guided Pre training
46	CML	Map building	Topological representation using correlation between online and stored images
26	CML	Map building	Motion computation by matching areas between pairs of consecutive images of a video sequence
78	CML	Map building	Taylor series of motion equations including second order terms

Table 3. Prominent topological Map-based Navigation Systems from mid 90s till late 2000

Authors	SLAM/ CML	Category	Method
77	SLAM	Map building	Appearance based matching with training set.
23	SLAM	Map building	Landmark tracking
41,57	SLAM	Map building	Histogram matching
61	SLAM	Map building	Appearance-based matching algorithms

Table 4. Prominent local map-Building Navigation Systems and obstacle avoidance from mid 90s till late 2000

Authors	Indoor/ Outdoor	Category	Method
4	Outdoor	Map building	Local Occupancy Grid
20	Outdoor	Map building	Local Occupancy Grid
25	Outdoor	Map building	Local Occupancy Grid
21,22	Outdoor	Map building	Local Occupancy Grid

3. VISUAL NAVIGATION FROM 2005 TILL PRESENT

Blanc et al [31] in 2005 provided their research for mobile robot navigation in indoor environment. Their approach was to train their robot during which it learns the environment as a graph of visual paths, called visual memory. They had mounted their robot with standard single camera for capturing images and then stored as set of ordered key images during training process. These stored images –topologically organized- provided the robot with visual memory of the environment. Navigation process started with providing an image as a goal. Its navigation mission is defined as a concatenation of visual path subsets called visual route. While running autonomously, the robot is controlled by a visual servo law adapted to its non-holonomic constraint. Based on the regulation of successive homographies, this control guides the robot along the reference visual route without explicitly planning and trajectory. However this system lagged the versatility to cope with dynamic changes in an environment which might occur after training phase.

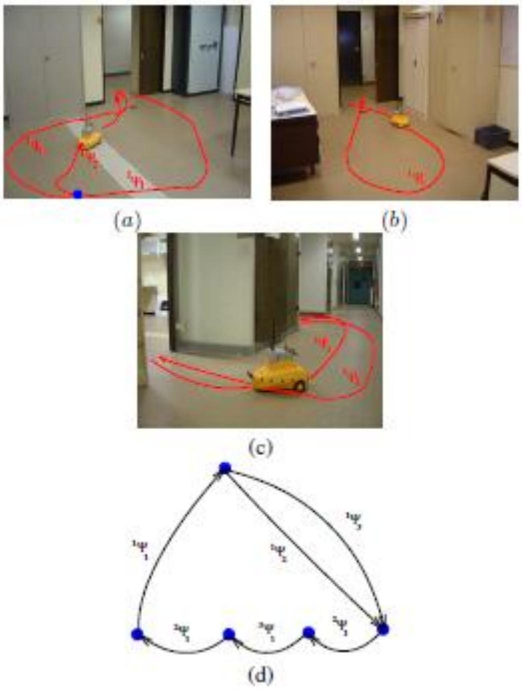

Fig 1: Building visual memory: into the rooms (a) and (b) and the corridor (c) the paths $^{r}\Psi_{p}$ have been learnt by the teleoperating the robot. As a result the graph (d) represents the topological organization of the visual memory. The blue circle show the vertices [31]

In 2009 Wen et al[18] experimented with visual navigation of mobile robot in indoor environment using artificial landmark system. In this normal paper marked with certain symbol were used as landmark hence it was easy to place the landmark in needed positions. These artificial landmarks were called MR (Mobile Robot) code. The shape of the MR code was designed to be an equilateral pentagon and binary BCH code was adopted for it due to which enough different locations, objects, etc with invariant characteristics under different viewing angles and illumination codes could be represented. Because of the nature of project this experiment was carried in structured indoor environment. Self-localization and navigation were done using this MR code.

Fig 2: MR code Prototype [18]

In 2011 Zhu et al[79] provide a paper to improve the performance of algorithm in real time and to reduce the cost of the system configuration. Its navigation was based on monocular vision for the application of mobile robot in

semi-structured environment. The method included image segmentation, information extraction and behavior decision-making. However with increase in obstacle in its workspace the robot could not function properly and move out of its course and loose itself in the environment. In order to solve the interference of the lights and shadows on the image segmentation, they presented an algorithm named ICAS (illumination-immune and Color Similarity-based Algorithm) by introducing similar measure, SIMILATION. SIMILATION is defines as Harmonic mean of values of a set over Arithmetic Mean which shows the level of similarity among a group of values. Mathematically SIMILATION is defined as:

SIMILATION=Harmonic Mean/Arithmetic Mean

In 2013 liam 0'Sullivan et al[43] introduced a new image based visual navigation algorithm which allows the Cartesian velocity of robot to be defined with respect to the set of visually observe features corresponding to previously unseen and unmapped environment. In this paper they described the general form of algorithm and also present simulation result in details for an aerial robot scenario using a spherical camera and a wide angle perspective camera and also present the experimental results for mobile ground robots. The contribution of this paper is control architecture for image based navigation or IBVN and it also provides drift-free vision-based station keeping and velocity control and the accuracy of the latter relies on estimating scene structure. The limitation of this research paper is that it has not been experiment on a different robotics platform (e.g. a quadrotor platform), using wide angle imaging and the navigating in more complex environment.

Cherubini [2] in 2014 provided with a framework for Visual Navigation and laser-based Obstacle Avoidance for a wheeled robot. It merges a reactive, tentacle–based technique with visual servoing, to guarantee path following, obstacle bypassing, and collision avoidance by deceleration. In it robot was trained for navigation by capturing series of images that need to be followed during navigation process. Obstacle avoidance was done using onboard lidar. Obstacle velocities were estimated using Kalman-based filter which were then used to predict possible collisions between robot and obstacle. The above method could avoid both static and moving obstacle which were absent during training phase. However this model could not predict occlusions produced by moving obstacles.

The use of neural network for various purposes like image processing and robotics were rising. By this time DeepNeural Network (DNN) and Convolution Neural Network (CNN) being used for various purpose. Christian Szegedy et al [11] utilized deep convolutional neural network architecture which they codenamed Inception. It improved the utilization of the computing resources inside the network. They increased the depth and width of the network while keeping the computational budged constant. Their experiments yielded solid evidence that approximating the expected optimal sparse structure by readily available dense building blocks was viable method for improving neural networks for computer vision. The main advantage was significant quality gain at a modest increase of computational requirements compared to shallower and narrower architectures.

4. CONCLUSION

There has been as tremendous progress in Robot navigation using various techniques. During yester years navigation using visual sensors were considered costlier in terms of processing and storage. Nowadays with new upcoming faster and dedicated image processors, compact imaging devices and compact storage unit visual navigation has taken a big leap in solving navigation problems to some extent. Now days complexity associated with SLAM and CML has also been mostly addressed and progress is still going on for better systems.

As if these were not enough, since the use of Artificial Intelligence in the field of image processing and object detection it has made Robot vision even better for use in real life scenario. Convolution Neural Network and Deep Neural Network has now started to be used for better robot vision.

Though new techniques has opened up many possibilities for robot navigation using visual sensors there are many more complex grey area to be looked at, most prominent being error detection and correction. There is no guarantee that visual sensors provide correct required image or video. Illumination, distortion, noise, occlusion and many more factors creeps in while processing image. After that object detection and classification has to be handled which also has its own cons.

Due to the vastness of this field there have been many researches in this area which has been provided above and many are still going on. This process of perfecting visual navigation process will still go on for many years to come.

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