Journal of Computer Science 5 (12): 948-955, 2009
ISSN 1549-3636

Vision Based Reconstruction Multi-Clouds of Scale Invariant Feature Transform Features for Indoor Navigation

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Abstract: Problem statement: Navigation for visually impaired people needs to exploit more approaches for solving problems it has, especially in image based methods navigation. **Approach:** This study introduces a new approach of an electronic cane for navigation through the environment. By forming multi clouds of SIFT features for the scene objects in the environment using some considerations. **Results:** The system gives an efficient localization within the weighted topological graph. Instead of building a metric (3D) model of the environment, it helps the blind person to navigate more confidently. The work efforts towards conceptualizing environment on the basis of the human compatible representation so formed. Such representation and the resulting conceptualization would be useful for enabling blind persons to be cognizant of their surroundings. The identification of different scenes to the blind person has done by clouds of three or two objects. These clouds grouped the stored objects into meaningful groups used in localization of a cane with single web camera as an external sensor. **Conclusion:** The approach is useful to divide the space environment into meaning partitions and helps to detect sites and objects needed from the blind person in very sufficient way with in the map.

Key words: SIFT, clouds of features, Image based navigation, localization, topological graph

INTRODUCTION

Intelligent machines are starting to move into human-occupied space and they will have a high degree of autonomy to effectively navigate from one place to another. Acquiring maps of the environment is a fundamental task for autonomous mobile robots, since the maps are required in different higher level tasks, such as navigation and localization. This map can be provided apriori or can be built by the robot as it explores the environment. Apart from navigation and manipulation, intelligent machines will have to understand, interpret and represent the environment in an efficient and consistent fashion. Path planning within the map is the process by which determining a feasible path to a goal. However this path some time is difficult to follow it, since the inaccurate movement of the robot, or the blind person. So this problem it needs a good consideration from the system to correct deviation from the intended path. The process of finding some image within this path is very important and it is called localization. The localization is done by the system when it compares the stored image with the current view depending on features matching between the two sides.

These features depend on techniques used like SIFT, Harris, SUSAN, SURF or others.

Recognizing some fixed object like door, windows, etc is also sit in localization subject. The localization process within the graph, is very useful for giving the system good information in the nodes which indicate the real world environment, due searching of the stored images graph. The information is always estimated not accurate 100%, but it near to a particular location in the graph. The situation in which an autonomous moving the mobile robot through an unknown space and building environment (map) while simultaneously using this map to compute its absolute location is called Simultaneous Localization and Mapping (SLAM). This problem has received significant attention during the past decades

At present, the vision based SLAM of the mobile robot always divides into monocular[2,16] and stereo vision[10,15], the two techniques depend on an important features extracted for localization. It includes some delay, comes from the initialization method, to recognize the initial landmark from the system, some system uses many images from different view point, for matching in the first stage and then determine the landmark and relevant information The correct

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recognition of the scene is important, for this initialization, what can be seen as distinctive and discriminative should be taken. For example, with indoor navigation, window corners are common scene, so they should not be considered as good features for scene identification. Features found on posters or signs are much better, although may be repeated elsewhere.

In this study the features for the objects are accumulated to form a cloud of features. The formed cloud it will be useful for further search of objects related in the same node, consequently the cloud will be rich of features due to detecting extra features for objects added to the same cloud, the idea comes when somebody searching for an object like TV, the search can be speed up, if there are other features relevant to the TV like Table, may be found will reach to required object, clustering objects into groups will have a useful job of dividing the environment into meaningful areas (clouds) This will extract more features for the neighbour of the object site and added as a reference for the same object and then the localization will be done more efficiently by these clouds. This also will help speed up the system to quick find objects according these clouds.

In this study a navigation system for the blind person using cloud of SIFT features approach will be described. The system navigates and localizes according to the clouds in the intended direction. It is an effort towards conceptualizing environment on the basis of the human compatible representation. Such representation and the resulting conceptualization would be useful for enabling the blind person to be cognizant of their environment; while traversing the nodes in the environment This type of representation is highly scalable and is also well suited to handle the data association problems that effect metric model based methods.

Related works: The requirements on a navigation system for the blind persons are unique; one of the main problems in indoor navigation is how to find the accurate position in unknown indoor environment. The subject heavily researched, the investigation continuous in this field; one can broadly dividing these works into two groups, the first group is based upon image processing and recognition[8]; the second group relies on wireless networking and sensor technologies as in[4].

Indoor navigation based graph representation is a good area for estimation and positioning which is referred to as Simultaneous Localization and Map building (SLAM) which is one challenge for the researcher in this field. Representing the real environment by a graph and using data structure using these graphs also has used in many researches like[4,20]. All of these works been concentrate on the features of the scenes. These features are extracted in many ways; the common ways are Harries and SIFT extraction of image features[1,8]. Many navigations used SIFT feature descriptors as in[9,20] other papers now proposed approaches for how to deal with the path planning in the graph for the robots, or games as in[4,13] search algorithms like A* and Dijkstra were considered for the path planning algorithm. The heuristic search like A* tries to find the cheapest path to the goal. While Dijkstra's algorithm tries to find a shortest path from starting node s to each vertex v in graph G = (V,E). Where the path planning algorithm is part of an overall navigation model At present, the vision based SLAM of the mobile robot always divides into monocular[2,16] and stereo vision[15,10]. The two techniques include delay. This delay comes from the initialization method, to recognize the initial landmark from the system; some system uses many images from different view point, for matching in the first stage and then determines the landmark and relevant information.

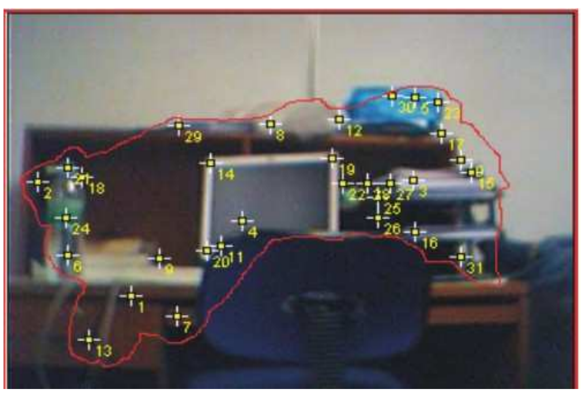
The one similarity between all these works is that all of them focus how to make a good navigation for the robot like human being navigation, i.e., all of them are built around the single application of robot-navigation. However this is good for the blind person but in another side the context of the environment will not be known by the robot and there is some failure to encode the semantics of the environment for the blind person. The focus of this study is how to make semantically environment representation for the blind person to navigate and recognize objects needed. Several other domains consider addressing this challenge; these include hierarchical representations of space, high-level feature extraction scene interpretation, the notion of a cognitive map and finally the field of Human Robot Interaction (HRI)[12]. The study presented here closely resembles those that suggest the notion of a hierarchical representation of space[11,12,21]. Recognition and add the detected objects to an occupancy grid map. The primary difference in the study presented here is that the proposed representation uses cloud of objects for future searching, i.e., the map is created and grown with the objects perceived.

MATERIALS AND METHODS

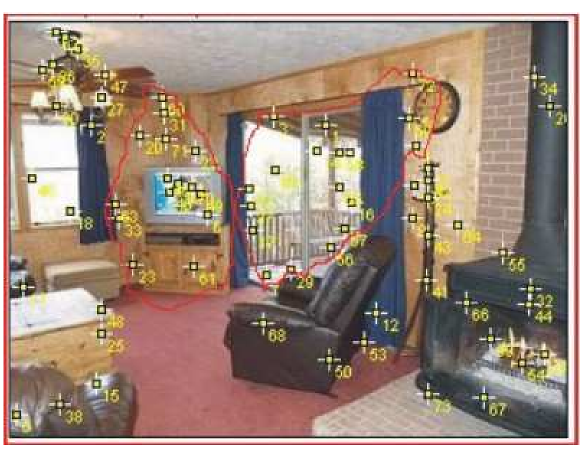
Model and clouds: The features for the scene will be constructed from the already stored features for the household objects to make a cloud of features for the scene. The content of the clouds depend on the scene taken (query image) by the web camera and matched with the stored feature database for the household objects in the site view. In other words the clouds differs from each other in concentration of SIFT features Fig. 1. Shows clouds of SIFT features constructed from features objects according to the side.

The site may contains more than one cloud constructed from objects taken in different consideration like direction side of the objects, or grouping the objects according to the session (as kitchen, bed and corridor,) or some objects important like door, window may take one cloud alone.

The process of cloud construction is more likely to that the blind person is close to the corresponding area in the node within the graph, this process is the localization of blind person in the graph. The graph contains a large collection of household object images, taken from all over the environment. The localization is performed by finding features for the household objects stored in the database related with current graph's node, which are similar to the current view image for the camera hold by the cane.



(a)



(b)

Fig. 1: Clouds of SIFT features constructed

The matched image features will be accumulated to construct a cloud. This helps that when the blind person re again recognize any object inside the cloud will help to recognize the other objects directly within the constructed cloud More than that, the position of the constructed cloud will be known with the objects inside it. The cloud is conceptualizing space on the basis of the human compatible representation. Such a representation and the resulting conceptualization would be useful for enabling blind person to be cognizant of their environments, The model is also uses appearance based approach as in[17-19], by memorizing a set of images taken from the environment for only the known objects stored in a temporary database within the graph of the environment for navigation.

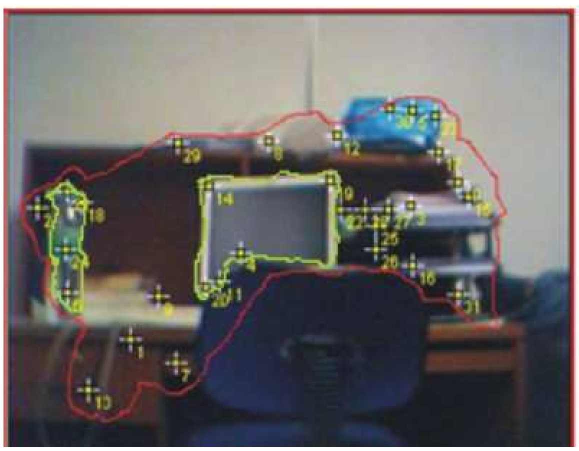
Cloud and nodes: In order to guide the blind person to their desired destination in a reliable and robust way, the system uses two kinds of features, the features for household objects to form the visual cloud and the whole features for all objects formed the visual cloud. The system calculates the weight for the objects inside the visual cloud, so it has the total weight of the cloud, this done using SIFT as in[3]. More details on SIFT-based object recognition can be obtained from[8]. According to the weight the system will recognize, localize and advice the blind person within the graph. The cloud can be formulated as c(I) = {f(O1),f(O2),….f(On)}, where, f(Oi) can be represented as a set of sift features f(Oi) = sift(Oi) = {fOi1,fOi2,…..fOin}, the cloud of the image I is C(I) and the order of the cloud is the number of objects inside the cloud, when the order of the cloud is high, indicates that the cloud is heavily of features for objects and then the site is rich of objects that known by the system. It is also important for the blind person to know the places of these objects inside the cloud. For example if the constructed cloud contained three sequential objects recognized by the system, then the boundary of the cloud can be represented as:

$$b(C(i)) = \int_{a1}^{a2} Oa + \int_{b1}^{b2} Ob + \int_{c1}^{c2} Oc \quad (1)$$

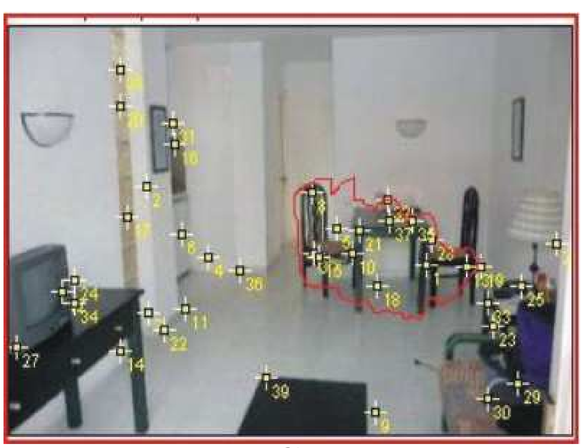
It is obviously that the boundary of the cloud start from least axis a1 to most axis c2 and the boundary for the objects may be overlapped, as in Fig. 2. Then the cloud boundary is representing all the objects inside the cloud.

This process is similar to localization using content based image process and this now is performing accurately and efficiently over millions of images[7,22], so this technique can be employed for fast localization.

The localization can be performed effectively using a household objects database in such a way compatible with the graph to speed up the construction of the clouds. The workspace environment representation as a weighted graph G = (V,E), will help to divide the database into groups of images as a node then the nodes will in turn grouped into clouds of images. The number of nodes in the graph is denoted by n and each node with its clouds v(c) € V contains household images at some pose in the workspace. The process of localization can be summarized here when the blind person navigating the environment, the site scene by the camera feed into the system to produce the cloud according to the objects inside it. This cloud will give the system information where the blind person exists. It is not so much accurate but at least the blind person will know a particular location is close, in the graph. The ideal localization would be robust to changes in direction, source (s) and intensity of illumination[22].



(a)



(b)

Fig. 2: objects features overlapped in the cloud

Object database, cloud table and landmark: In our study we build a database of objects with their sides in the node an image of object is captured and SIFT descriptors are computed and stored along with their image positions X0. The estimated real pose of the object oi inside the database is tried as (xi, yi, θi), the image not need be fronto-parallel. To obtain relative pose estimates between the stored object and scene object inside the cloud, the essential matrix E between the two views of the same object is computed using the 5 point algorithm[7,22].

The cloud table is a table of all temporary clouds constructed in the system, due the navigation of the blind person, within the nodes, where the system referenced the object inside this table to know the other objects in the same cloud. The table referenced by a composite key of indexes for objects. The cloud of order two will include zero component instead of the missed object inside the cloud, the cloud of order two will has two zero component, this explained later on The clustering object into a cloud involves representing the blind person's environments as a large set of features, some features are very important to navigation process The construction of cloud with some determined objects features can be set as a landmark Landmarks are parts of the image which hold sufficient information about the image[12]. Usually small set of landmarks per images is needed. This study a SIFT based object recognition used, one characteristic of the SIFT is that it does not learn any general properties of objects in order to categorize and classify them; it depends on the local features for the object to recognize The arrangement of the objects in the cloud is just as generalizing the features inside the cloud for the site in front. For example when talking on the door, shall remember soon the lock of the door and the edge, the neighbor environment of the door is also effect to recognizing the door inside the cloud. Figure 3a shows the cloud contains a local landmark.

Saving temporary clouds consequently will give the system good information about the objects and neighbors, such that when recognizing package the system knows from the constructed cloud is the door beside of it, this is a good way of learning the blind person surrounding environment. Suppose the node within the graph storing many clouds of order 2 or 3 $n(i) = \{c_1^2, c_2^3, c_3^2, \ldots\ldots c_i^3\}$ the cloud constructed:

$$C_1^1 = c_1^0 + f(O_i) \quad (2)$$

$$c_1^3 (I) = \{f(O_1), f(O_2), f(O_3))\}$$

Where:

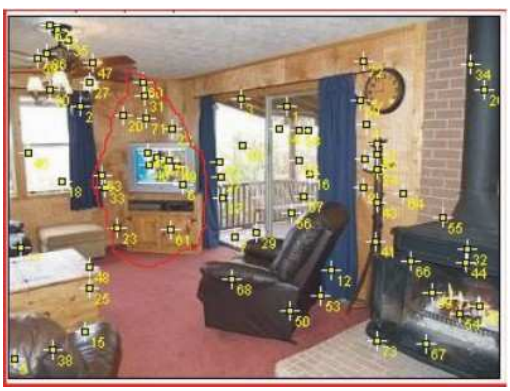
I = The query image
c = Cloud
f = SIFT feature function for any object

$$m(c_1^3(I),f(O_2))=p(f(O_2)/C_1^3(I)) \quad (3)$$

where, m is matching function, for the probability of existing SIFT features for object O_2 inside cloud C_1.

This leads the system knows c1 which contains also $f(O_1)$ and $f(O_3)$. It is essential that the object inside the clouds not repeated to speed up the system. Then the landmark will be found quickly. The process can be represented in Algorithm illustrated in Fig. 3b.

The blind person cannot be controlled for any direction as done in the robotics and also the cane cannot be focused in a specific view point. For that reason this model treats the scenes as a set of cloud SIFT features SIFT was developed by David Lowe for image feature generation in object recognition applications[6,8]. The SIFT algorithm compromise 4 steps: Scale-space extrema detection, keypoint localization, orientation assignment and keypoint description.



(a)

For current node
 Take the next scene view
 Do{
  Recognize an object in the same side
  If object found in the cloud table
   Then fetch the cloud content
   perform Localization process
  Else
   Add the recognized object to
   temporary cloud.
   perform Localization process
  } While objects remaining in the view
 Add new cloud to cloud table

(b)

Fig. 3: Recognition of Landmarks and cloud forming

These features are invariant to image translation, scaling and rotation and partially invariant to illumination changes. It depends on Gaussian function G for scaling space function L:

$$G(x,y,\sigma)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{1}{2}\frac{x^2+y^2}{\sigma^2}} \quad (4)$$

$$L(x,y,\sigma)=G(x,y,\sigma)*I(x,y) \quad (5)$$

and the DOG is a function that gives the difference between two scales σ and kσ:

$$\begin{aligned}D(x,y,\sigma)&=(G(x,y,k\sigma)-G(x,y,\sigma))*I(x,y)\\&=L(x,y,k\sigma)-L(x,y,\sigma)\end{aligned} \quad (6)$$

The scale space is separated into octaves; when the cloud used the site view will be subdivided and then the time complexity will be decreased.

Computational efficiency of localization using clouds: An object can be represented as a set of visual parts of the object or related to it the navigation for the same place, it needs recognizing only one object, this will fetch the cloud containing recognized object with other objects which are already stored in the cloud, without any more calculations. This will speed up the system and give some indications for the blind person that the system knows other objects in the same area, Table 1 shows the time elapsed for matching one site view which contains objects queries using cloud model for the purpose of localization process using SIFT.

The cloud can apply for the other techniques like Harris, SUSAN and SURF. But SIFT used here for the mentioned reasons. It is essential to know the position of the objects inside the cloud and also the position of the constructed cloud within the node. The localization here is to know the blind person is near to a particular location in the graph this referred to as qualitative localization[22] The model creates weights according to overlapping between the real environment scene site and the already stored feature for household objects in the system database Weight for the cloud depends on the number of objects inside it and how much these objects overlapped.

Table 1: Time elapsed for the objects matching

Object	No. of key point match	SIFT sec^{-1}	Cloud of SIFT sec^{-1}
Package	8	2.146653	0.786438
Bottle	7	1.956542	0.896191
TV	23	1.293581	0.987788
Chairs and table	65	1.169922	0.722027

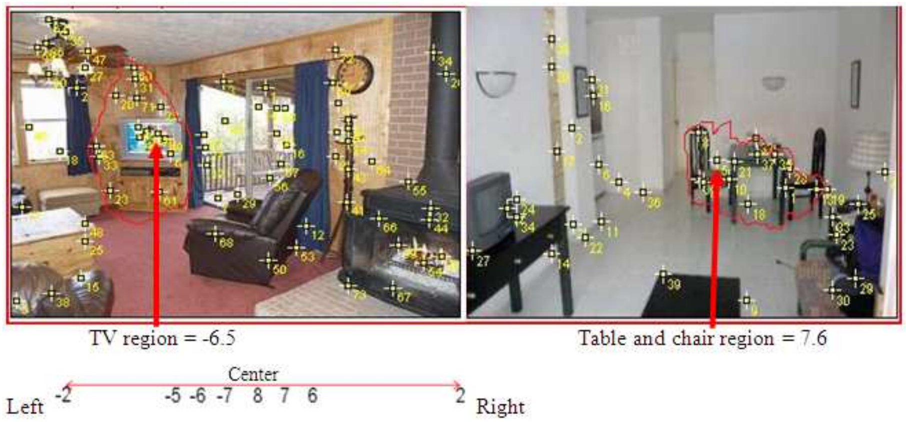


Fig. 4: Features and scalar weight values

The weight of the object inside the cloud is the extent range of the object inside the cloud, in this study x-axis horizontal has been considered to know the range of the object. This weight may changes due changing view point of object appearance in the view and introducing new objects, this in turn will effect of the cloud itself. The scalar value of the weights for objects arranged from -2 to 2 according to rule, if the overlapped features concentrated either left, right, or center of the view. The 8 value of weight indicates the centre of the view and values near from the 8 will be near from the center. While negative weight values indicate to the left side of the view and positive weight values indicate to the right, as shown in Fig. 4. In this study the blind person moves in (x,y) plane and may rotate about the z axis. The estimated real pose of the object oi inside the database is tried as (xi, yi, θi) the actual pose between the oi and oj in the cloud is (xij, yij, θij), this is polar coordinates is equivalent to:

$$(rij, yij, \theta ij)$$

Where:

$$rij = \sqrt{(xj - xi)^2 + (yj - yi)^2}$$

$$yij = \arctan\left(\frac{yj - yi}{xj - xi}\right) - \theta i$$

$$\theta ij = \theta_j - \theta_i$$

The estimated relative pose is $(\hat{r}_{ij}, \hat{\phi}_{ij}, \hat{\theta}_{ij})$ to obtain relative pose estimates between the two objects oi and oj, the essential matrix E between them is computed using 5 point algorithm[7,22].

Separated clouds at same time in one node, formed when the blind person's direction is towards a corner between two sides in the node, further considerations can be taken to form clouds for future studies. Also the kinds of the clouds can conclude the session in work[3]. The auditory system here is informing the user location and obstacles according to the formed cloud and advising the user the direction It is also very suitable for robotics system to navigate according clouds to anywhere in a known position.

RESULTS AND DISCUSSION

Graph represented here is that, each room of the environment is a node. Set of nodes (laboratory room, corridor) are V, the way (door) leads to other rooms are edges E with weight W In realistic scenarios for environment of the system, the blind person will navigate from one place (like the laboratory) through the corridor. The system matching stored object's images with the environment, to construct clouds for the matching objects and store it in cloud table as training phase of the system to learn the environment, then the system will work for mapping by the appearance based graph. The two ways access objects done by seeking first on the objects inside the cloud table. If it exist all objects inside the entire object cloud will be known, otherwise a database will be accessed to construct a new cloud then added to cloud table as a new entity. The system meanwhile advise the blind person to navigate anywhere according to the internal process, with in the node in the graph. The rich cloud of SIFT features giving the system more reliable. Weights for objects inside the clouds give more flexibility to the system.

The system started with a node has a set of images for objects taken at certain positions in the environment for the node with known side directions. The calculated weights of scenes environment and cloud construction, gave the estimated position and the direction of the blind person as a localization process for the system in the graph. The new cloud constructed after recognition objects and then checked if it is already exist in the cloud table or not. Indexing of the clouds has done according to the object's index in the database. The individual indexes merged together as composite key to form the index of the cloud. For example if the cloud contains (package and door), the index of the cloud will be (current node + index of package + index of door + third object no present→ (n1+12+4+0→ n10120400) zeros separated the components of the cloud index in the table. Figure 5 shows a sample of image taken in the experimental environment for navigate the blind person. The system consistently shows good on-line performances for environments, the image for the object stored as features of SIFT to be directly match with the image scene used 320×240 jpg format, low quality with a good rate of correct recognition above 50% depending on the specific environment difficulties. The new cloud of objects added to cloud table with in the experimental work in the laboratory the average of objects recognized with in the clouds ranged from 1-3.

The referencing of the cloud table with in the node is reducing the time for seeking local landmarks, since the landmarks will be known to the system when recognizing objects in already stored cloud in the table. Referencing one object mean that accessing many objects within the cloud. The good matching of the landmarks is that when the site view with cloud of needed objects, comes in the center of the camera, (i.e., the weight will be high), this will let the system directly recognize the needed objects in the node. Also the site view with more than one cloud formed is useful to know which direction the blind person has taken then to give advices accordingly.

This would result in a very inflexible trajectory which would be useful to traverse in a dynamic environment. Also this technique can be used in outdoor navigation for limited space.

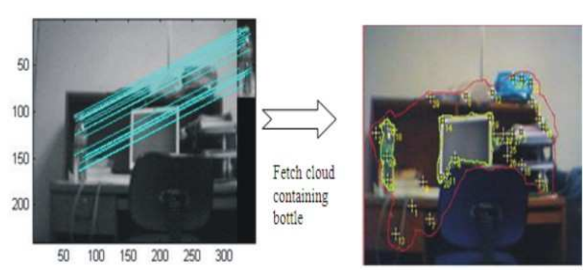


Fig. 5: Sample images from the system

CONCLUSION

In this study, we described a method that extracted features from the site view using SIFT algorithm, we established an algorithm to conceptualize the environment using clouds of features with SIFT techniques. The clouds helps to quickly locate the objects in the environment, this in turn speed up the localization process within the environment, the model is try to give semantic of the environment due forming these clouds of SIFT features for the objects. It is useful to divide the space environment into meaning partitions according grouping objects then it helps to detect sites and object needed from the blind person in very sufficient way with in the map.

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