3D Tracking in Industrial Scenarios: a Case Study at the ISMAR Tracking Competition

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***Abstract*—One of the most challenging tasks in augmented reality is to develop a tracking system for industrial scenarios. This is due to the fact that this environment has characteristics that defy most of the techniques available, such as textureless objects that in some cases are too large and in others are very small, as well as may be very close to each other or occluding themselves. This work proposes the combination of established techniques for 3D reconstruction and tracking, as well as a calibration routine, that is suitable for this type of scenario. This complete tracking system was validated at the ISMAR Tracking Competition, a contest that simulates industrial scenarios and is promoted to challenge state of the art trackers. The case study simulated a manufacturing task in which the environment was divided into five areas, and the user had to be guided by the tracking system through these areas collecting specific objects from an area to put them at a specific location in another one. A discussion regarding the tracking system results is lodged , aiming to introduce an analysis that could help others during the development of their own tracking systems for industrial scenarios.**

***Keywords*-augmented reality; industry applications; 3D tracking;**

I. Introduction

In recent years, Augmented Reality, or simply AR, has received attention as a field that is changing the way people interact with the world. In order to relate virtual content with the real environment, AR systems are built based on tracking techniques that can discover in real-time where the virtual information should be added [1].

In industrial scenarios, tracking techniques can have several applications. They can be used to help an operator to execute a maintenance task [2] or to allow a machine to analyze a product [3]. Unfortunately, industrial scenarios are often difficult to track since they may have poorly textured objects with lots of smooth surfaces. Strong light variation is also a difficulty, as well as the size of equipment that may be very small, among others.

When developing a tracking system for industrial scenarios, a model-based approach is usually chosen because of its precision [4]. However, if a model-based tracker is employed, it is essential to associate it to an automatic reconstruction process that will generate the 3D information to be tracked. Besides that, a correct calibration between the generated model and the real world may be necessary to relate the world coordinate system with the reconstructed and tracked coordinate system.

In order to achieve a solution capable of dealing with some major difficulties in the industrial scenario, this work explains the integration of a 3D model-based tracker with a reconstruction from images technique and a calibration routine. This tracking system was validated at the ISMAR Tracking Competition, which aims to challenge state of the art trackers through a simulation close to a real world scenario. In the particular edition where our tracking system was used, the contest simulated a manufacturing situation, which is part of many industrial environments. From the analysis of the contest it was possible to discuss many problems encountered in the industrial scenario. As far as the authors know, there is no work discussing the use in industrial scenarios of an integrated tracking solution using well known techniques for reconstruction, calibration and 3D tracking. There is also no work discussing the ISMAR contest and relating it to the industry field. Another important contribution of this paper is to share and discuss the experiences and challenges found during the development of a tracker for an industrial scenario. Therefore, this paper provides a starting point for anyone interested in engaging into these problems from a practical point of view.

This paper is organized as follows. In Section II recent advances in 3D tracking, reconstruction and calibration techniques are discussed; the development of an integrated solution for generating 3D models, calibrating coordinate systems and tracking is explained in Section III; Section IV details the case study performed at the ISMAR Tracking Competition; the result of the integrated solution at the competition is analyzed in Section V; the lessons learned about how to build a tracking system for an industrial scenario are discussed in Section VI; finally, in Section VII, major conclusions are drawn and potential future work for tracking in industrial scenarios arises.

II. Related Work

There are several ways to track objects. It can be accomplished using only RGB cameras or adding other equipment such as depth sensors [5], magnetometers [6] and inertial sensors [7], to name only a few. The 3D tracking system presented in this paper is a monocular one, and therefore major state of the art techniques are discussed in sequence for tracking, reconstruction and calibration based on video, focusing their application to industrial scenarios.

A. Tracking

Video based tracking can be classified in two categories: recursive tracking, where a previous pose estimate is required for computing the current pose of the object; and tracking by detection, where the object pose is calculated without any previous estimate. While recursive tracking is often faster and/or more accurate/robust, tracking by detection allows automatic initialization and easy recovery from failures. Existing techniques for natural feature tracking and detection can also be classified as model-based or model-less. Model-based methods make use of a previously obtained model of the target object [4]. Model-less techniques are also known as Simultaneous Localization and Mapping (SLAM) methods [8], since they estimate both the camera pose and the 3D geometry of the scene in real time.

Model-based techniques can be classified regarding the type of natural feature used [9]. The recursive tracking methods can be divided in the following categories: edge based, where control points sampled along a 3D edge model of the object are matched with strong gradients in the query image [10]; template based, which aim to estimate the parameters of a function that warps a template in a way that it is correctly aligned to the query image [11]; and local invariant feature based, where local features that are invariant to distortions such as rotation and illumination changes (e.g. Harris corners [12], Good Features to Track [13]) extracted from both model and query images are matched [14] [15]. Model-based tracking by detection methods can be classified in the following categories: edge based, which make use of specific edge representations for detecting and estimating the pose of target textureless objects [16] [2]; and local invariant feature based, which rely on matching local invariant features extracted from model and query images, even if they were obtained from significantly different viewpoints [17] [18].

B. Reconstruction

Since the model-based methods are a common approach for markerless tracking, the acquisition of the 3D model of the target object is an important step. Sometimes the target object is very simple to be modeled manually, such as a plane or a box. However, it is unlikely that in the industrial scenario the target objects will be that simple. Manually modeling these complex cases is a difficult task and could take too much time, so it may be necessary to have an automatic 3D reconstruction of the target object.

There are several ways of making an automatic 3D reconstruction. One of the most efficient and precise approaches is using laser scanners [19]. With this equipment it is possible to generate a dense 3D model of an object with millimetric precision. The downside is that these lasers are expensive and sometimes it is hard to use them to reconstruct places difficult to access because of their size and weight.

Another automatic 3D reconstruction method is based on structured lights [20]. This technique consists in projecting on the scene light patterns that are previously known. Then, a camera captures the projection of these light patterns. The 3D model is calculated based on the distortion of this projection. Since this technique requires only a simple camera and a common projector, it is quite inexpensive, especially when compared with the laser approach. However, structured lights reconstructions are much more imprecise and impossible to be used in a bright environment, such as an outdoor area during day. Figure 1 shows the result obtained by this type of reconstruction.

The image based 3D reconstruction method is one of the most common approaches to generate 3D models automatically. There are also different techniques to make this kind of 3D reconstruction work, such as SfM (Structure from Motion) [21] and SLAM [8]. What these techniques have in common is that they take 2D images of the scene and use them to generate the 3D model as shown in Figure 1. Usually that process can be done by employing a feature detector that could be the same as the one used during the tracking. Nowadays there are several image based reconstruction techniques that achieve good precision [22]. Even though it is also a cheap approach since it only needs a simple camera to take pictures or make a video of the scene, this method is often very hard to reproduce.

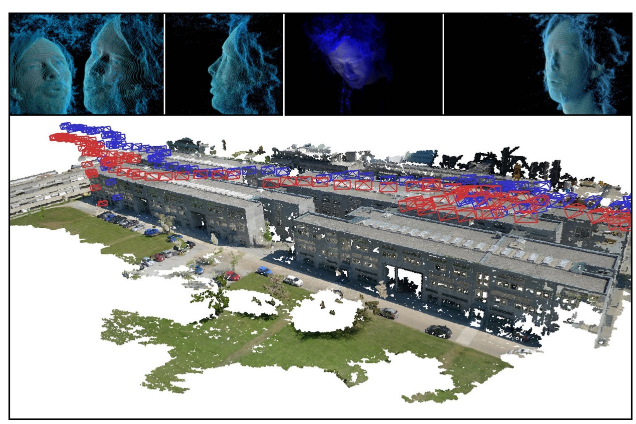

Figure 1. On the top row there are different views from a 3D model generated using a structured light approach; on the bottom row, a building reconstructed using the SfM technique.

C. Calibration

In AR applications, it is sometimes mandatory to have a coherent scale between the 3D reconstructed model and the real world coordinate system. For example, in an industrial scenario the equipment are modeled based on their real scale and could be used to augment the scene [2]. Based on projective geometry properties, even with calibrated cameras in which the intrinsic parameters are known, it is not possible for a technique based only on images to directly achieve a metric reconstruction without some input from the user. The automatic 3D reconstruction from images is an up-to-scale process and just returns a similarity reconstruction of the object [23]. Only techniques based on depth sensors are able to achieve a metric reconstruction directly since they acquire from the depth sensor a real depth during the capture process [24].

For a 3D reconstruction based on images there are several ways to achieve a metric reconstruction. If the user knows some 3D points from the scene and is able to correctly relate them to the similarity reconstructed points, it is possible to find a calibration matrix that can take all the up-to-scale points to the metric reconstruction system [23]. When the user has a previous 3D reconstruction of some object or part of the scene it is possible to match these 3D models and use an absolute orientation process to estimate the correct alignment between them and use these information to get a metric reconstruction [25].

III. Industrial Scenario Tracker

In general, the nature of objects appearance in industrial scenarios favors the use of edge based trackers since the edge information in these objects is more evident, and usually they have low texture information, as seen in Figure 4. On the other hand, it is hard to perform real-time detection of objects based only on their edge information. In addition, for an edge-based tracker, when there is a crowded group of objects, it is harder to identify each object separately. The occlusions and the high number of nearby edges makes difficult the task of correlating the searched edges with the ones present in the scene. At last, in order to track each object edges, it is needed to acquire in advance its 3D model definitions, which is not always possible, and so an automatic reconstruction phase is preferred.

Figure 2. Typical industrial scenario in which most of the equipment are textureless and with edges well defined.

Taking into account all these issues, the presented tracking system is based on invariant keypoints extraction and matching. Even though the use of this approach is recommended for high texturized scenarios, these keypoints are also able to describe low texture objects as long as there is enough color information in the whole scene. It aims to perform real-time detection and tracking of complete complex scenes by using an automatic 3D reconstruction based only on images. Beyond, the system is able to automatically initialize and recover from failures. This feature is highly recommended for industrial scenarios since the user of the tracking system, being a human or robot, may navigate and focus on not traceable scene regions. In addition, the use of invariant keypoints enables the tracking of the scene as a whole, being not restricted to planar scenarios or single objects tracking. Furthermore, a metric calibration is also necessary to applications that need to relate real coordinates from the scene and the tracked models.

A. Tracking

The implemented tracker presented here is mainly based on the work of Gordon and Lowe [26] and can be divided in two phases: an off-line step in which the 3D model to be tracked is generated and an on-line stage that consists in keypoint extraction, description, matching and pose calculation steps. The off-line phase will be discussed in the next subsection.

The first step of the on-line phase consists in extracting and describing 2D keypoints from the current image using the Scale-Invariant Feature Transform, better known as SIFT algorithm [17]. SIFT keypoints are invariant to scale, illumination and viewpoint changes, being more suitable to track objects with high color texture variation on its faces. However, as it will be discussed in the results section, these keypoints are also able to describe low texture objects as long as there is enough color information in the whole scene.

After extracting and describing the SIFT keypoints, the system matches the current image keypoints with the set of keypoints from the reconstructed model acquired in the off-line phase. This matching is done by a best bin first search algorithm with the help of a kd-tree to speed-up the process.

Even with all the robustness of the SIFT matching, some points could be wrongly correlated, resulting in outliers. To remove these bad matches, the tracker was improved with a technique that is able to validate keypoints orientations, even when out-of-plane rotations occur [27].

Given a set of matches, it is possible to assign a 3D coordinate from the model for each matched keypoint. Thus, the pose calculation can be performed using a set of 2D-3D correspondences, in which the 2D points come from the image and the 3D are from the generated model in the off-line phase. This knowledge allows the pose calculation in each frame, independently of the previous results, guaranteeing a detection behavior of the tracker and allowing it to automatically recover from tracking failures. The pose estimation is calculated by using the RANSAC algorithm allied to the EPNP estimator [28].

B. Reconstruction

After the analysis of some constraints from a general industrial scenario environment, a video based approach was chosen to generate the 3D model of the scene. For instance, the tracking scene may be very bright, that invalidates the use of a structured light technique. In other situations, such as a small warehouse, it is difficult to use a laser scanner because of its size. Besides, this type of equipment is very expensive, as mentioned before.

There are several image based 3D reconstruction tools available, some of them are commercial, some are commercial with free use for academic purposes and others are academic. Most are based on SfM technique and need only a few images as input to generate the 3D model. Based on a comparison of the principal tools [29], the VisualSfM [30] was chosen as reconstruction tool.

Some reasons were determinant to select this tool. One is that it uses SIFT features in the reconstruction process, which is the same used by the chosen tracker, as mentioned before. Because of that, most of the reconstructed 3D points come from 2D points that have a high probability to be also extracted by the tracker, which makes the matching phase more stable. It is important to notice that the VisualSfM is the tool that produces the point cloud with the greater quantity of points from the ones analyzed. To maximize even more the extraction of correspondent points, it is a good practice to take the pictures that will be used by the VisualSfM with the same camera that will be used in the tracking phase.

Another advantage of the VisualSfM is that it exports the model as an ASCII file that has the projection matrix for every image used in the reconstruction and all the tracks found in the process. A track is a set that contains one 3D point and all the correspondent 2D points used to generate it. The track also contains one image for each one of the 2D points. So, this file is loaded and this information is converted to the data structure that will be used in the tracking phase. It is also possible to export the model as .ply, a common file format for 3D models.

The VisualSfM tool has a free license policy for personal, non-profit, or academic use as long as the tool is not modified and the VisualSfM authors are referenced, which is the case for this work. For commercial use, the VisualSfM authors must be contacted for an appropriate licensing.

C. Calibration

In order to achieve a metric model to be tracked, the presented tracker system employs a calibration phase based on the work of Hartley and Zisserman [23]. Since the VisualSfM provides a reconstruction ASCII file with all intrinsic K_j and extrinsic parameters $[R_j|t_j]$ for each reconstructed camera j, it is possible to combine these information with 2D points matched in a subset of the images set $(m_{j=0}, m_{j=1}, m_{j=2})$ to correctly approximate its 3D coordinates M^{sim}, a known process called triangulation [23]. Figure 3 illustrates this procedure. In our tracker for industrial scenarios, a subsystem based on manual intervention was implemented to achieve this goal.

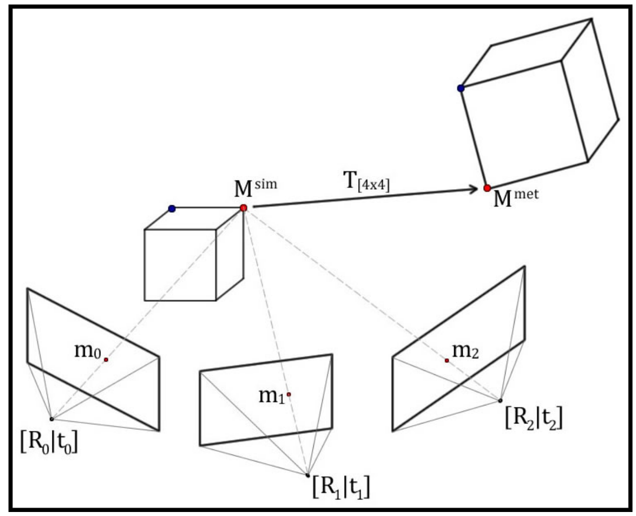

Figure 3. Triangulation and Calibration.

After the triangulation it is possible to correlate the 3D triangulated points $(M_0^{sim}, M_1^{sim}, ..., M_i^{sim})$ with known 3D metric points $(M_0^{met}, M_1^{met}, .., M_i^{met})$ in order to estimate a transformation matrix $T_{[4x4]}$. This matrix can be applied to all 3D points in homogeneous coordinates and take them from the similarity model to the metric one. The metric points M_i^{met} are loaded from a calibration file provided by the user with the correct measurement in real world coordinate system. As the transformation matrix is estimated by a linear system, there are necessary at least four correspondences between similarity and metric points to achieve a unique solution.

IV. Case Study

The evaluation of a tracking system in AR applications is not an easy issue [31]. Many efforts have been done in the past years to provide metrics and standards to analyze the aspects related to this problem [32] [33] [34]. Since 2008, the International Symposium on Mixed and Augmented Reality (ISMAR) promotes the ISMAR Tracking Competition, a contest aiming to challenge state of the art trackers through real world problems, therefore stimulating breakthroughs in current solutions. All the scenarios prepared for the competition try to replicate real problems for tracking systems, such as lighting conditions, task specificities, user constraints, levels of texture information available, objects relative size, camera resolution and others.

In 2012 the ISMAR Tracking Competition simulated a manufacturing task in which the environment was divided into five areas. The user, simulating a worker, had to be guided by the tracking system through these areas collecting specific objects from an area to put at a specific location in another one. The only input for the tracking system was the 3D coordinates of the objects to be picked up and the position where they should be placed. Each area was composed by one table with specific objects placed over it. The level of difficulty was different for each table, depending on the size, shape and texture of its objects. These five areas can be seen in Figure 4.

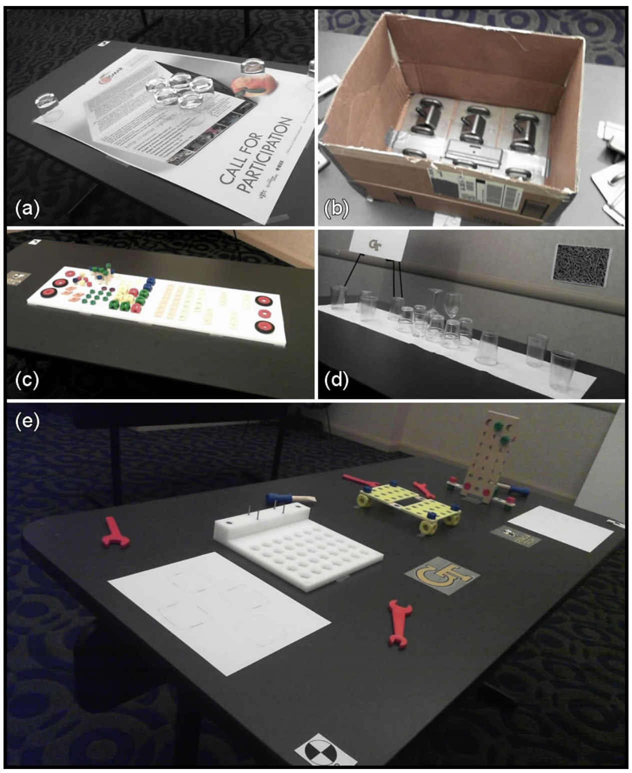

Figure 4. ISMAR Tracking Competition manufacturing scenario: (a) texturized planar poster with eight drinking glasses over it; (b) cardboard box with metal pieces inside and surrounding it; (c) plastic white board with several small pieces with different shapes, sizes and colors; (d) white planar paper with glass goblets and plastic cups; (e) table with the position where the picked up objects had to be dropped.

Figure 4 (a) shows that over the first table lied a texturized poster of the ISMAR conference to simulate the simpler case of a textured planar surface. There were also eight drinking glasses in order to disturb the tracking by adding refraction effects, which means that the number of outliers may be enlarged since most of the techniques are not able to deal with such artifact. Often industrial scenarios provoke the presence of outliers even with robust feature detection and matching, as discussed in the section above.

The table seen in Figure 4 (b) had several metal pieces, some inside and others outside of a cardboard box. The goal was to simulate areas that are difficult to access. Another difficulty for the tracking system was the fact that they scrambled the objects outside the box after the calibration phase as an attempt to simulate small scenario changes between calibration and tracking, a possible problem in manufacturing environments.

The table in Figure 4 (c) simulated a typical manufacturing scenario with several small pieces, some different from each other and some with the same size and shape. These characteristics made it more suitable for edge based techniques and represent a common problem at many industrial scenarios which is the absence of textures and the similarity between objects.

In the table shown in Figure 4 (d) the organizers created a tricky scenario with several glass goblets and plastic cups over a textureless table. This table simulates the case in which there are objects over a planar surface with well-defined edges. An edge based technique would suffer because of the glasses and a texture based is not suitable for this textureless environment, but a simple homography based planar tracking is capable of handling this scene.

The last area, seen in Figure 4 (e), was the target table. It had several objects and locations for putting the objects coming from the previous tables. Some of them were close to each other and others were superposed. Since the objects picked had to be dropped in one of these objects or space locations, it analyzed the tracking precision. This table was also composed by both textured and textureless objects. This was the most important table since all the objects had to be dropped there, given half of the score points in the competition.

The contest runs during two days, being the first one dedicated to the setup phase. Each team was allowed to explore the room, calibrate their system, test and adjust their tracking algorithms before the competition. In order to calibrate the system, all teams received a file with the metric coordinates of the 3D points corresponding to all markers placed in room. These markers had just the function to enable the calibration and could not be used to help the tracking.

The actual competition happens in the second day. Every team receives a file with the 3D points of objects that have to be picked up from the four first tables and the position where they must be dropped in the last one. The system has to guide the user through this task, simulating the real world manufacturing scenario.

V. Results

The presented tracker was developed in C++ using data structures and basic functions from the OpenCV [35], VXL [36], DSVideoLib [37] and OpenGL [38] libraries. The IDE used was Microsoft Visual Studio 2010. The competition rules state that the tracker system must run using any device that only one person can carry and still be able to pick up the objects. Thus, the device used was a notebook with Intel Core i7 processor having 4 cores of 2.3 GHz each, 8 GB of RAM memory and the NVIDIA GeForce GTX 670M graphic card. The Microsoft LifeCam Studio webcam provided the video and image input for tracking and reconstruction, both with 640 x 480 pixels resolution.

Firstly, the reconstruction quality was evaluated, since it is very important for an accurate model-based tracker. In the setup phase several pictures of the tables were taken to be used as input for the VisualSfM. As mentioned before, the camera used in the reconstruction was the same as for the tracking phase. There are not an ideal number of photos to be used.

The first decision to make was to use a single big reconstruction for the entire room or to use one reconstruction for each table. If using a single reconstruction the calibration just have to be done once and tables that do not need to have many visible markers around each to be calibrated. That could speed up the process and minimize the chance of not having all tables calibrated. The problem on this approach is to achieve a reconstruction that contains all tables. The Visual SfM tends to maximize the quality of the reconstruction by splitting it into a set of reconstructions, generating one reconstruction for each set of images that contains many textured elements in common. That means that would be better to reconstruct each table separately. Thus, the authors tried to use the minimum quantity of pictures possible that could generate an adequate reconstruction of most of the tables. This is due to the fact that the higher the number of photos the longer the time to perform the reconstruction [29].

In this case, there are not metrics or values defined that can attest with certainty that the reconstruction result is adequate, but indeed there are some indications that can guide the evaluation process. One of them is the number of images that the Visual SfM used for the reconstruction. The number of 3D points composing the model tends to increase since more pictures were used to feed it, degrading the performance. Additionally, the reconstruction was also visually evaluated by the percentage of the whole scene reconstructed and the number of points that do not fit to the real world (outliers). In some cases the result was not good enough to enable the tracking. When that happened, more pictures were taken and a new reconstruction was made using the original images in addition with the new ones.

Figure 5 shows the reconstruction result for all tables. In most of them the 3D model generated was visually coherent with the real scene. Only the reconstruction result of table (d) was not good, because VisualSfM uses texture information to generate the 3D model and this table does not have this characteristic.

The tracking system used in the competition performed in real-time, with a FPS of 29.41 for a 320 x 240 resolution image and 20.94 for a 640 x 480 frame. As mentioned before, the goal was to pick up objects from four of the five tables and drop them at a specific location in the fifth table. The system was able to track every table individually, as can be seen in Figure 6. However, the authors had problems to align some of the reconstructions with the defined coordinate system, being able to pick and release the objects from the tables a and e that were correctly calibrated. An important matter was that the calibration system used needs the 3D point in metric coordinates of at least four non-coplanar markers in each provided table. For most of the tables it was not possible to reconstruct all of the needed markers. In some tables there were just two or three easily visible markers. The others were too far from the table or were in another one.

Every table simulates a different situation in the industrial scenario, presenting different challenges. For instance, table (a) represents the most common case for texture based trackers, which is a planar textured pattern. The addition of drinking glasses represented an addition to number of outliers in the system by the refraction. However, since a large area of the poster remained unaffected by the refraction, the tracker was able to keep tracking correctly a sufficient number of features in order to calculate the final pose. The pose also showed a good precision because the outliers generated by the refraction related error were discarded either in the outlier removal or in the RANSAC processing steps.

The goal with table (b) was to collect one of the metallic pieces in the interior of the box. Even though there were several of these textureless objects, the SIFT algorithm was able to extract and match the features required. This was probably because the overall scene was treated as a large textured pattern. Besides that, the box itself had some texture on it, which helped the tracking technique. After the setup phase, the competition organizer changed the metallic objects that were outside the box. This simulates a situation in which workers would change the environment during the tracking. Since the box and the pieces inside it did not change, the tracker should rely only on these parts of the table. In Figure 6 it is possible to see that several features were extracted from those areas.

On table (c) there was a set of organized small colored pieces. Tracking each piece separately is a non-trivial task for texture based trackers. However, since the pieces are grouped in the same scene region, the overall area generates traceable textured patterns which can be detected by the SIFT extraction. The repetitive nature of the arrangement on this table maybe an issue but in this case the repeatability is not massive enough to nullify the distinctiveness property of the extracted features.

Table (d) is specifically hard to track using keypoints

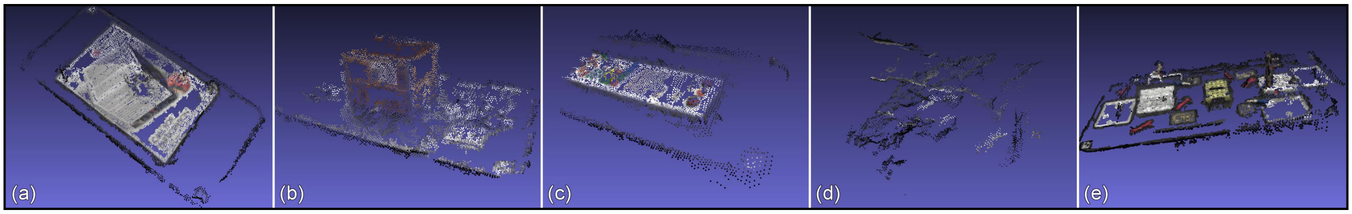

Figure 5. The reconstruction result for every table in the tracking competition. Tables (a), (b), (c) and (e) could be well reconstructed using feature information. The exception was the table (d), that is textureless.

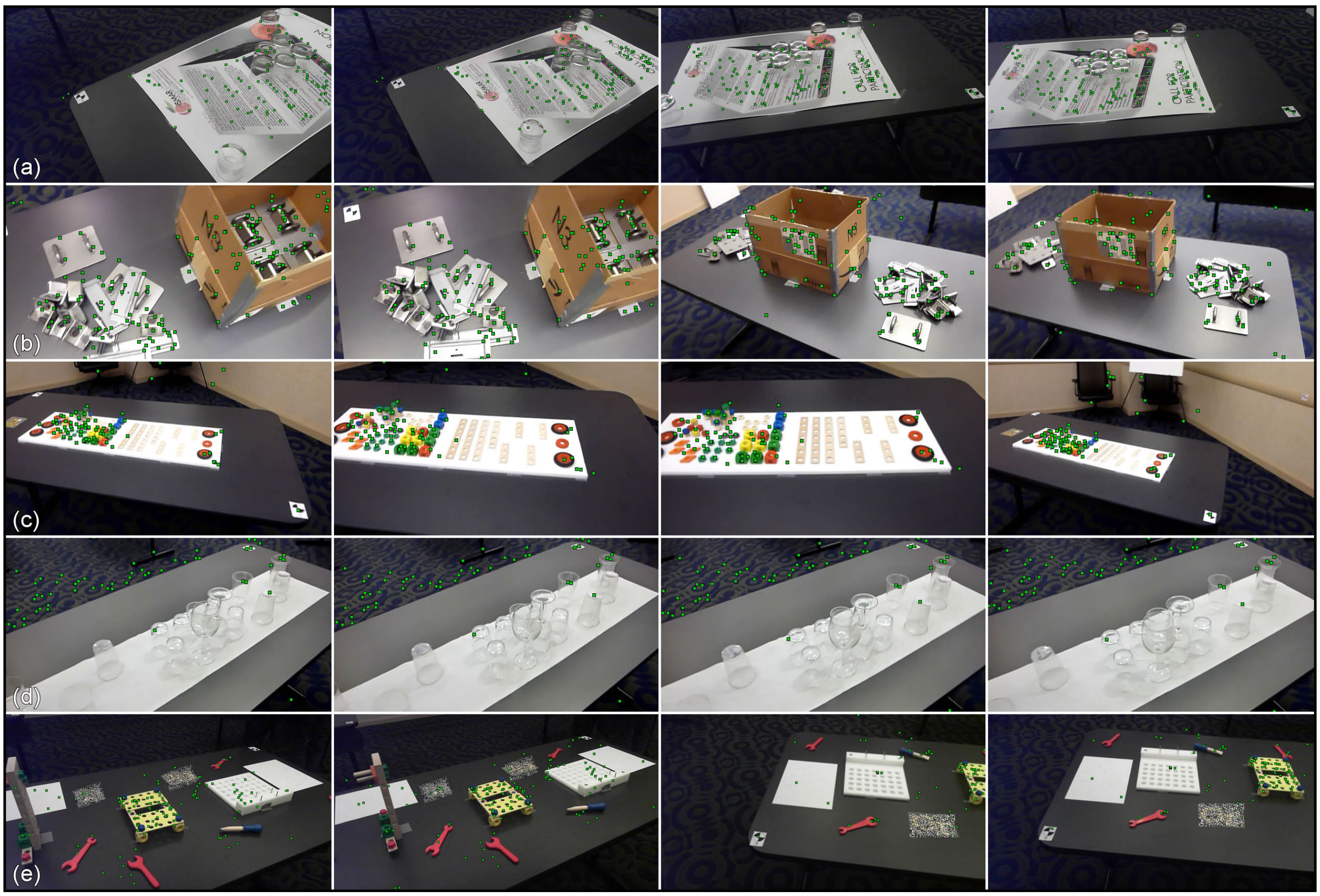

Figure 6. Each row shows four frames of the working tracker on a different table. The green dots are the features extracted in the frame that match with keypoints detected in previous frames.

information. This table setup is composed mainly by a white table cloth and a set of glass goblets and plastic cups, containing almost no reliable color information. Figure 6 shows that only few features are tracked over the table itself. However considering the overall scene information, sometimes it is possible to reconstruct and track determined scene by using not only the targeted model but also additional parts of the environment. This way, it is possible to perform a sort of environment tracking, in which the tracking procedure can match keypoints with other scene regions than the model itself. In this case, due to the presence of the textured pattern from the floor, SIFT keypoints were extracted and matched, making it possible to track the camera position in the scene even without a rich textured model as a target. This kind of tracking is not ideal since it is needed to fit more elements in the captured frames, other than the aimed model, however it turns to be an alternative to guide the user in these difficult scenarios.

Finally, table (e) presented an intermediate scenario between table (c) and table (d). It presents a few non-textured objects over the table. These objects are generally bigger and more complex than the ones presented in table (c), which makes possible the identification of features even without crowded scene parts.

The overall results of the presented tracking procedure showed to be reliable in different scenarios regarding specific issues like refraction, self-occlusion, non-textured targets, planar and non-planar cases and dealing with both, crowded scene regions and sparse objects distribution.

VI. Lessons Learned

The authors learned some important lessons from the experience of researching, developing and validating a tracker system for an industrial environment. By sharing these lessons learned with the community, the authors believe that it might help others researchers to prevent errors or anticipate problems in the development of their own tracking systems.

First of all, the image based reconstruction is very important for the final result. Without a good reconstructed model it is almost impossible to have a good tracking based on models of the target objects. For achieving a good reconstructed model there are often required more matches that for the tracking itself. In order to consider a reconstruction result a good one for tracking, there should also be observed aspects such as percentage of the whole scene reconstructed and types of objects reconstructed, number of wrong reconstructed parts, number of points that do not fit to the real world (outliers) and number of images used in the reconstruction. For more complex scenes it could be necessary to use more images and this could slow down the reconstruction process. Thus, it could be interesting to insert textured patterns on the scene for the setup phase in order to improve scene reconstruction. There is a chance that the tracking phase can succeed without having the textured patterns present on the scene just because the reconstruction is better.

The calibration is a very critical step for the tracking to work properly, since it is necessary to have enough reconstructed images with the calibration points visible on them. One approach that helps to solve this problem is to force the reconstruction algorithm to not discard some defined images, warranting that the final reconstruction result used them. Another possibility is to reconstruct subsets of two or three tables together to simplify the calibration. It must warrant that the four required calibration points appear in it. As discussed before, a possibility is to use a reconstruction for the entire room but to do so the system must use a 3D reconstruction tool that does not split the reconstruction in small sets. Sometimes it is not possible because of the distance or obstacles between industrial areas. Since it could degrade the reconstruction result it deserves a deeper analysis.

Another important point is to do the calibration in a reverse way. Instead of calibrating all the models and then tracking the complete calibrated model, it is better to track using the non-calibrated model and change the virtual information to be added using the inverse calibration. This procedure maintains the tracking more stable because the calibration process could add error to the model.

The automatic focus and exposure control of the camera will also add problems to the process. There are some software as the Microsoft Lifecam that can be used to control and fix these parameters manually. Sometimes because of the lighting changes the algorithm gets lost and just comes back when the focus and exposure stabilizes.

During competition it was also noted that the system should give feedback to the user regarding tracking quality, since industrial scenarios can have many similar objects near each other and the user can be fooled by an incorrect guidance caused by a tracking failure. Due to that, a message was displayed in the title bar of the application in order to inform the use if tracking was correct or not.

VII. Conclusion

This work presented and discussed a complete system that is able to reconstruct, calibrate and track industrial scenarios. The main advantages and drawbacks of this procedure were analyzed based on its results at the ISMAR Tracking Competition that was used as a validation case study for the system. Besides that, this paper provides a comprehensive analysis of several aspects related to the development of a tracker system for industrial scenarios. Thus, this article can help other researchers and developers that are engaging in a similar task.

As future work, it is fundamental to improve the calibration phase of the system. Wrong calibration can lead to tracking failures and imprecision. The use of more point correspondences or more images in which the points are visible may produce a better result.

In order to improve the tracking phase, the system can employ an edge based technique that will help to achieve a more stable multi-feature tracking (edge + texture). In case of using a mobile device as an interface for the system, the tracking quality can be improved by taking advantage of the device sensors, such as the inertial, GPS or magnetometer.

VIII. Acknowledgments

The authors would like to thank CNPq, FACEPE and Reuni-UFPE 01/2012 for the scholarship of some members of this paper (process 141853/2011-5, process 551388/2010-2, PBPG-0547-1.03/11 and process PBPG-0660-1.03/09), as well as the funding of our MCT/CNPq Universal project (process 475975/2009-0).

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