Workplace Assistant Augmented Reality

[Review Report]

Gabriel Camilleri
Dr.Vanessa Camilleri
Faculty of ICT, BSC Honours Artificial Intelligence
Msida MSD 2080
0021299M
gabriel.camilleri.17@um.edu.mt

ABSTRACT

Starting a new job in an office can be very stressful for an intern or a new employee, especially on their first day at the office. It takes time to adjust and learn what other employees' jobs are and how they can be beneficial to them. It might additionally take some time for new members to learn the ropes and their purpose within the office building, while understanding and learning how to use certain equipment, for example, an automatic key lock or simply a coffee machine. Therefore, the Workplace Assistant Augmented Reality tries to identify the user's requirements in accomplishing a specific task within the workplace through user profiling and recommendation, whilst providing the relevant information for the user to learn and understand the environment around them via augmented reality. The application is intended to guide new employees through an adapted process which enables them to understand the environment around them along with equipment which they might use daily. It will also be intended on guiding the users, providing them with relevant information in order to successfully accomplish their task. The system incorporates collaborative filtering and a similarity-based technique using SVD++ and item to item based similarity respectively, to provide recommendations, along with deep learning and traditional computer vision techniques using Vuforia, to provide augmented reality. Using the tools mentioned the system provides information about offices, directions towards specific offices, and information on how to utilise the coffee machine of the company which the application was tailor made for. From the tests performed the indication is that the SVD++ model was the most efficient model to apply in comparison to other machine learning models, when applied with AR. The model achieved average Root Mean Square Error and Mean Absolute Error of 3.1226 and 2.6866, respectively. The AR component achieved promising distance, colour, rotation and occlusion variance values. Finally, the system obtained on average positive qualitative results via user-feedback along with recommendations on how it may be further improved.

Keywords

Augmented Reality, Workplace, User Profiling

1. INTRODUCTION

Starting a new job in an office can be very stressful for an intern or a new employee, especially on their first day at the office. It takes time to adjust and learn what other employees' jobs are and how they can be beneficial to them. It might additionally take some time for new members to learn the ropes and their purpose within the office building, while understanding and learning how to use certain equipment, for example, an automatic key lock or simply a coffee machine. "Person-job fit is a substantial factor for decreasing job stress and the adjustment of employees to an organization is an important issue for eliminating stress"[1]. In a research carried out by P. Moita [2], is discussed how new employees start a new job with high expectations due to several factors such as previous jobs or promises made during recruitment. The first month at the workplace might seem overwhelming for new employees. Therefore, during their first few months of settling and adjusting, the company may allow "a period of learning how to 'fit in' and adjusting to how things work in the new setting"[2] for the employee's benefit.

Providing an assistant AR application to help speed up the process for the employee to adjust to their new workplace environment may offer several challenges. There are several AR libraries which provide all the necessary techniques for one to build such applications. However using algorithms, techniques, and models which involve A.I, may help in overcoming those challenges in image and object recognition. For instance, "[t]he SIFT algorithm deals with the problem that certain image features like edges and corners are not scale-invariant. In other words, there are times when a corner looks like a corner but looks like a completely different item when the image is blown up by a few factors"[3]. Therefore one can combine the algorithms mentioned with deep learning techniques to allow the application to recognise real world objects as efficiently as possible,without hindering the user's experience.

2. AIM AND OBJECTIVES

The aim of this project is to combine user profiling techniques with image and object detection and present these in an Augmented Reality application designed for the workplace.

The objectives of the final year project are:

- Perform image and object detection techniques using the Vuforia Library;.
- Use AR techniques from the detected images and objects to overlay and augment information, providing office and work equipment information along with directions towards a specific office of interest.
- Develop user profiling techniques through a recommendation based system to filter out unnecessary information for augmentation.
- Apply and evaluate the developed and implemented artificially intelligent techniques through quality and quantity testing.

3. LITERATURE REVIEW

3.1 Workplace Augmented Reality

> [A]ugmented Reality (AR) technology has rarely been discussed outside of the computer science world. It has taken years for this technology to become closer to a stable existence, and will most likely take several more years before it will be used by average citizens.[4]

Although the technology can be considered still in its infancy, it also has a wide variety of applications. One of its main applications in the 4.0 Industry is the use of AR in assisted learning. Every workplace necessitates adjustment and some form of training for employees to adapt to the process of the work they might be doing. AR may assist employees by providing them with additional overlaid instructions to guide them through the whole process of adjustment while providing them with training.

Workplace training is usually provided in two forms, namely, on the job training (OJT) and off the job training. “[O]JT may be viewed as an apprenticeship where a novice AMT is mentored by an AMT who is an expert” [5]. This is the traditional form of training, especially when teaching maintenance. However, “[O]JT may not be the best method for training because the feedback to learners may be infrequent and unmethodical” [5]. Conversely, off the job training may be provided through face to face conversations or through multimedia. AR can combine the two aspects of training, where the user is given on the job training through multimedia, which overlays the real-world environment.

There are several useful applications for AR at the workplace. However, not every workplace might necessitate AR. “[T]here are situations where an AR system may be used to enhance the task completion process, or display and/or communication of information in conjunction with traditional technologies” [4]. As discussed in [4], the following are workplace conditions where AR is applicable, namely, distance communication with 2D or 3D objects provided for visualisation, training and education when using real-life tools, recording of information obtained while training, and a collaborative design and interaction of 3D models.

An advantage which AR offers to workers and managers is “[t]he ability to author their own environment by embedding the relevant information needed for task completion” [4]. Nonetheless, a common problem during work training is that the expert individual needs to provide the respective information to the trainee in the most understandable way possible. Therefore, through AR technology, the trainee can tailor how that information is presented, and thus, AR may be capable of understanding its users such that it may adapt to future possible users.

3.2 Recommendation Systems for Augmented Reality

Information during job training is crucial for an employee to learn and adapt to the new environment. However, an overwhelming amount of information provided to a new employee may be demotivating. AR is a tool that provides interactive information to the user while also obtaining information from the user. Nevertheless,

> ...[t]he fact that the typical scene of these applications mix real and virtual elements can be a motivating factor for users. However, this feature may also make the interaction more complicated, which can affect the user experience in performing tasks within the application.[6]

“[R]ecommender systems (RS) have proven to be a valuable tool for online users to cope with the information overload” [7]. Recommendation systems provide tailored information to different users based on their preference. “[T]hus, it is important to offer the user a personal response, but also a context-dependent and constrained by the limited computing capacities of the mobile devices” [7, 8, 9, 10]. Therefore, the recommendation system should provide its user with information which might be of interest to them, but which also makes sense in the context and location they are using it.

Collaborative filtering techniques have been widely adapted in recommender systems. According to [11], an SVD++ algorithm performed best when applying collaborative filtering when applied to the MovieLens dataset. However, traditional recommender systems in AR cannot be easily adapted and deployed since they differentiate in the following areas: location, timing, first time use of the application, and immediate response from the AR application, as discussed in [12]. Distance-based filtering and visibility-based filtering are commonly used in AR. In [12], a random walk algorithm was incorporated, whose recommendations are based on user preferences, behaviour patterns, history records, and information from social media. However, in the latter research, user feedback was not evaluated, which would have helped to provide the efficiency and performance of the AR recommender system. An alternative to using location or distance-based recommendation, AR applications can make use of time-based recommendation systems, that is, the amount of time one would generally take to complete a task using the AR application. A task may take extensive time to be completed by the user due to several factors, such as, the task itself is complicated, or simply, the AR app is incapable of providing the user with the right instructions and guidance to solve the task, simply because it may lack different forms of interactive techniques. The study by [6], defines "[a] set of procedures to conduct experiments with users to identify how a set of aspects related to the user role can be considered to improve mobile AR technology usage". The result of this research is that young groups of people spent less time completing a task using AR since they were accustomed to similar forms of technology. On the other hand, users with little to no experience and those of an advanced age took obviously longer to adapt to the technology. This was due to several factors, other than being newly introduced to such forms of technology, one such example could be health issues which can hinder their overall performance, such as, eyesight problems and motor coordination.

3.3 Computer Vision Approaches in Augmented Reality

AR applications make use of several CV approaches to recognise images, objects and text. As previously discussed, Vuforia makes use of both traditional and deep learning approaches. Using deep neural networks ensures highly accurate and efficient results. However, "[i]t is well-known that training high capacity models such as deep neural networks requires huge amounts of labelled training data"[13]. Neural networks are data-hungry architectures that require huge amounts of data to train and test on, thus being capable of generalising accurately.

As discussed in [14], marker-based applications have been the main driving force to apply AR in real life. "[M]ost of the current approaches to 3D tracking are based on what can be called recursive tracking" [14]. Therefore, the system must be initialised manually, and with some occlusion between the camera and the object being recognised, the system fails to perform. However, a new CV approach has improved AR, and can register the camera without camera pose introduction. This approach is called Tracking-by-Detection, and in [14], it is tested to determine its benefits. The approach works by extracting feature points from inputted frames during run-time. The features are then "[m]atched against a database of feature points for which the 3D locations are known"[14]. However, there were still key limitations, such as, detecting reflective and shiny surfaces on the car, since not many features could be extracted. Another limitation was dealing with occlusion, especially if a person were standing anywhere near the object being detected.

According to the research conducted by [15], a S-G Hybrid Recognition method was implemented in order to solve the occlusion problem within current AR technology. The approach takes "[a]dvantage of robustness of the SURF feature-based object identification and combine it with high reliability and effectiveness of the Golay error correction code detection" [15]. SURF and SIFT are two traditional vision approaches, commonly used for feature-based detection. The advantage of SURF is scale and rotation in-variance. Golay error correction code, on the other hand, is a marker identification approach.

> A marker based on the Golay error correction code (ECC) can be composed of a large white square in the top left corner and e.g. 24 black or white squares that encode a number. The large square provides information about the marker orientation. [15]

The researchers tested the three main aspects which may hinder an AR application, namely, distance variance, angle variance, and occlusion. Consequently, through the S-G approach, it was found that an object can be placed 2m away from the camera, while the comparison of the angles was completely influenced by the SURF algorithm which was able to detect under 55 degrees angle to the camera's axis, and that it could not be affected by up to 55% obstruction.

Another approach to solve the occlusion problem in AR is to apply deep learning techniques, as described in [16], where the researchers "[p]resent a temporal 6-DOF tracking method which leverages deep learning to achieve state-of-the-art performance on challenging datasets of real world capture" [16].Deep learning architectures can be trained on large amounts of data thereby solving occlusion, angle variance, and distance variance problems. Their approach involved getting a 3D model of the object and training the tracker for that specific object. Training involved two steps; firstly, using a frame to capture the object in its predicted position, and secondly, the frame of the object's actual position. "[T]o encourage the network to be robust to a variety of situations, we synthesize both these frames by rendering a 3D model of the object and simulating realistic capture conditions including object positions, backgrounds, noise, and lighting" [16].

Deep learning architectures work well when making use of GPUs. The GPU is commonly used to run deep learning neural networks; hence, the network takes less processing time to train and test. The study by [17] presents "[Y]OLO-LITE, a real-time object detection model developed to run on portable devices such as a laptop or cell phone lacking a Graphics Processing Unit (GPU)". YOLO-LITE is primarily designed to obtain a smaller, faster, and more efficient model. "[Y]ou Only Look Once (YOLO) was developed to create a one step process involving detection and classification. Bounding box and class predictions are made after one evaluation of the input image"[17]. The developed architecture runs at 10 frames per second, and its goals are to prove that shallow networks can run on non-GPU devices, and that shallow networks do not require batch normalisation. The model had 18 trials, obtaining results of 33.77% mAP and 21 FPS, and 12.26% and 21 on PASCAL VOC and COCO dataset, respectively.

4. METHODOLOGY

The AR application is divided into four separate parts. The first part is the data extraction process, where data is collected for training, both for the AR aspect of the application, and for the recommendation process. The second part involves feature extraction, where relevant features are extracted and fed to the implemented or applied model for training. The third phase entails building a suitable user-query model for user recommendation. The last part is implementing the trained data within the custom-built user interface to provide a user-friendly AR experience.

4.1 Data Handling

The data extraction process is further divided into three phases. The first phase is gathering relevant images of the area around the workplace, while phase two entails building 3D models of chosen markers for the AR. These 3D models must capture as much detail as possible of the actual marker. The images and 3D models are then fed into Vuforia's Library for training. The third phase is gathering data from a good number of previous users who rated the application when they performed a task. This third phase is necessary in order to perform collaborative filtering techniques using a set of machine learning algorithms and probabilistic methods to achieve a set of user preference recommendations. The yielded results are subsequently combined with the item to item similarity-based matrix.

4.2 Feature Extraction

The first step in the feature extraction process was feeding the images into the Vuforia library which extracts features from them, as shown in [18]. The library applies natural feature extraction to identify contours and edges from within the image, and consequently, display a 5-star rating according to how augmentable the image is. In this case, images of the door signs were used as markers due to their static look and nature. The second step was feeding the 3D models into the model target generator. Vuforia's object recognition utilises natural feature tracking by analysing the object at 3 different axes. The model target generator trained a total of 11 markers, which consist of the coffee machine and the door markers. The final step is extracting the features from the prototype built datasets of user-ratings.

4.3 User-Query Recommendation

4.3.1 Item to Item based Similarity

The item to item similarity-based recommendation consists of a matrix which stays constant and represents the similarity between one location and another, based on whether the user passes right in front of it when trying to find an office. The selected locations were the accountant's office, the human resources office, the manager's office, the secretary's office, the kitchen, the restrooms, and the games room. Each row was computed using the term frequency approach. TF was chosen to enhance the relevant importance of a sought query, in this case, the office one wants to go to. Finally, this matrix is combined using the dot product with the user query matrix.

4.3.2 Collaborative Filtering Techniques

The collaborative filtering approach is a model based on the user's past experiences of the decisions taken, locations of interest picked, and task they had in order to complete their own task.the system uses a Single Value Decomposition Plus Plus provided by the Surprise library. The decision to apply SVD based algorithms instead of PCA or CA-CF was to achieve a higher accuracy [19]. The top three predicted ratings' 'LocationsOfInterest' are then stored in a csv file and fed into Unity, hence these are the top three user-query matrices.

4.4 System Architecture and User Interface

4.4.1 System Architecture

There are three main components which make up the system architecture. The first most essential component is the user, who is important as the system must serve as an essential tool to assist them around the workplace.The second component is the recommendation system which, as previously explained, provides collaborative and similarity based filtering techniques, depending on the user's profile. The third component is the AR provided by Vuforia. The built architecture within Unity consists of three features. The first feature is called 'Offices', which allows the user to wander around the workplace and view augmented information from the office markers. The second feature is 'Locate', which offers office information and offline directions to the user, depending on their preferred recommendation. The third feature is 'Coffee Machine', which provides employees and visitors with information on how to make use of the coffee machine. This information is provided through text, images, and video instructions.

4.4.2 User Interface

The user is presented with a main menu, allowing them to augment information about the coffee machine, or the offices while wandering around, or to locate an office. The coffee machine interface is augmented once the coffee machine is recognised, allowing the user to learn how to make a cappuccino via an augmented video and text. The offices information interface is augmented once the user's phone recognises the correct marker, allowing them to view details about the office or locate a particular office from where they are. Navigation is not provided through an artificially intelligent algorithm, and it is not within the scope of this research to implement it. Navigation is provided through a 3D sketched holographic map which gives an idea of where the visitor or intern needs to go to find the office.

5. EVALUATION AND RESULTS

5.1 Augmented Reality Quantitative Evaluation

The AR component was evaluated using four types of evaluation methods. The first test was color variance testing, the application managed to recognise all image and model targets in color and black and white. The second evaluation method was distance variance. The application obtained an average of 130cm and 150cm for image and model targets respectively. The third method of evaluation was orientation variance, where the system obtained an average of 360. The final method of testing was occlusion variance, where the application's capability in recognising an obstructed target is tested to its limits. The object was occluded by 25%, 50%, and 75% horizontally. The system obtained an average of 55% and 64% for image and model targets respectively.

5.2 Recommendation System Quantitative Evaluation

The initial step of evaluating the recommendation system was plotting data distribution charts of the data generated with regards to the user ratings. The data plotted shown that there was no bias towards a specific user's preference or a specific task/ location of interest. The second step of evaluation was baseline comparison using a 5-fold cross validation. The SVD++ model was compared along with

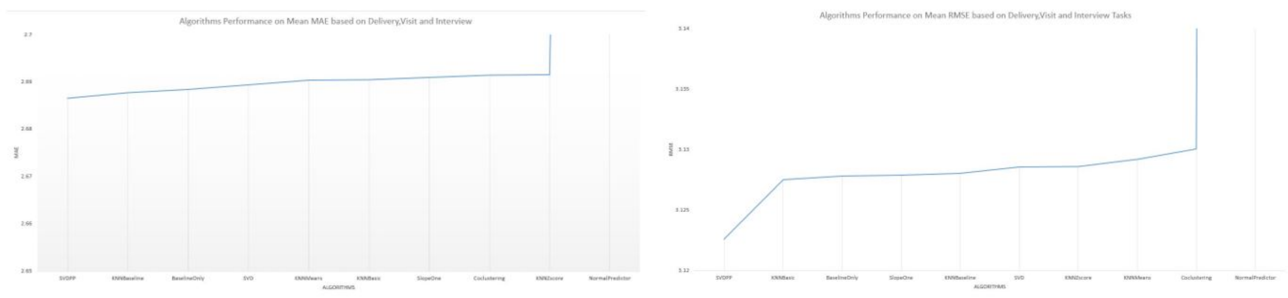

Figure 1: The graphs showing the MAE and RMSE values obtained by each model

'KNNBaseline', 'Baseline', 'SVD', 'KNNMeans', 'KNNBasic', 'SlopeOne', 'CoClustering', 'KNNZscore', and 'NormalPredictor'. The models were compared using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as values. The SVD++ model in comparison to the other models on average performed best on both set of values as shown in figures 1. It measured the least amount of average magnitude errors during prediction. Therefore, the algorithm was the most accurate.

Finally, the hyperparameters for SVD++ are tuned using the grid search method. The GridSearchCV() method provided by Surprise library calculates the RMSE and MAE values for every combination of hyperparameters using, in this case, a 5-fold cross-validated dataset. Finally, it returns with a set of correct parameters that improve the model's accuracy.

5.3 Qualitative Testing and Evaluation

A survey was carried out in order to collect user-feedback with regards to the overall system's performance. In total 30 participants took part, 15 of them were the company's employees, whilst the other half ware not. All participants found the application assisting for completing a given task. On average the application along with the augmented information was found helpful especially by the workplace's employees. The interface was given an average 5-star rating of 3.9 for it's user friendliness. Overall most employees found the application easy to use, especially non-employees. However, one main feedback provided was that the 3D Holographic map was seen as somewhat confusing. The recommendation system earned an average 5-star rating of 4.27. It is notable that all non-employees did not find it confusing to understand its functionality, whereas 33% of the workplace's employees did find it confusing. It is also promising that 63% of the participants did not see occlusion as a major drawback of the application's performance. Therefore, this comes to show how efficiently the application works when markers are occluded. Overall participants found the AR system natural and realistic to use, enabling them freedom of interactivity and movement.

6. CONCLUSIONS AND FUTURE WORK

6.1 Future Work

There are a number of recommendations which we can list as possible future work to build upon this research.

- The company should be encouraged to initially make use of a smaller type of dataset or simply use a random walk algorithm. Gradually as the dataset increases Deep Learning techniques may be applied for recommendation. The research done in [20], proposes an alternative to SVD++, where the deep learning model converged faster and achieved better RMSE values
- To allow users to interact with the real world through AR, as proposed and tested in [21]. This may be applied to the workplace to book offices for meetings by recognising the office door sign marker and interacting with the company's shared calendar.
- The inclusion of location based AR may enable the users to see real time holographic and augmented information while walking around the workplace. This may be applied via strong indoor positioning systems, such as, proximity-based, WIFI-based, ultra-wide band, acoustic, or infrared systems. However, one then would need to make use of other AR libraries, such as, ARCore or ARkit, instead of Vuforia since it does not support location-based AR. An alternative would be creating photorealsitic models of the interiors and applying deep learning for training to recognize features depending on the current location one is in.
- To include explainable AI which provides a set of tools and frameworks to implement machine learning models which can easily be interpreted and understood by the users. One can easily understand certain decisions taken by the artificial intelligent models rather than merely be presented with their results. It improves transparency with human-interpretable explanations, hence providing any patterns found within the applied models.

6.2 Conclusion

To conclude, this report presented an approach to applying a workplace assisting augmented reality using Vuforia's traditional CV methods, and deep learning approaches, combined to work harmoniously together. The main challenge was using the right markers to apply image or object recognition to. An initial approach was to augment the entire corridor with information using image targets, as previously explained, large spaces of environment are prone to constant change by day, which will ultimately affect the AR application's efficiency and the user's experience. Furthermore, Vuforia had difficulty recognising most corridors since they had no distinctive features to recognise. Secondly, applying collaborative recommendation was a challenge as the correct model and techniques had to be applied. One main limitation was due to the fact the no pre-existing datasets of user-ratings existed within the company, thus it was decided to build the datasets simply to prototype the application. However, the built datasets were based on norms carried out within the workplace. Finally, a challenge and a limitation was to improve markers recognition without having to pan the smartphone due to switching from traditional CV techniques to deep learning techniques when augmenting information about offices. The main cause behind this was, due to the fact that Vuforia and Unity lacked the feature to make use of multiple model targets in one scene. Hence, why a workaround was made by allowing an image target to activate the respective model target, thus allowing the application to make use of multiple model targets sequentially.

In total, 11 markers were used from the first floor of the workplace, and were subject to qualitative testing by employees from the company, as well as external people who did not work there. The quantity testing carried out on the AR component has shown the limits of the application. It has successfully worked well when tested on distance, rotation, occlusion, and colour variance achieving on average positive results. The recommendation and user profiling system was successfully implemented, obtaining positive results in terms of accuracy and performance with an average fit time of 0.1053 seconds and average test time of 0.0023 seconds. The results obtained are not surprising and are indeed promising, highlighting the fact that AR can be applied to the real world using the techniques mentioned in the objectives. It was thus beneficial to achieve successfully the results. However, one should not ignore or overlook the fact that there will always be room for improvement and innovation.

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