Real-time Object Detection and Tracking in Mixed Reality using Microsoft HoloLens

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Abstract: This paper presents a mixed reality system that, using the sensors mounted on the Microsoft Hololens headset and a cloud service, acquires and processes in real-time data to detect and track different kinds of objects and finally superimposes geographically coherent holographic texts on the detected objects. Such a goal has been achieved dealing with the intrinsic headset hardware limitations, by performing part of the overall computation in a edge/cloud environment. In particular, the heavier object detection algorithms, based on Deep Neural Networks (DNNs), are executed in the cloud. At the same time we compensate for cloud transmission and computation latencies by running light scene detection and object tracking on board the headset. The proposed pipeline allows meeting the real-time constraint by exploiting at the same time the power of state of art DNNs and the potential of Microsoft Hololens. This paper presents the design choices and describes the original algorithmic steps we devised to achieve real time tracking in mixed reality. Finally, the proposed system is experimentally validated.

1 INTRODUCTION

In the late '90s, Augmented Reality (AR) was popular in the research field and its potentials and applications in the real world were already well-known (Azuma, 1997). The idea of being able to increase our understanding of the world simply by observing something, has encouraged the research in the field, suggesting lots of practical applications. Thanks to recent technical advances, these kinds of applications are becoming even more popular. In this work, we exploit a modern Head Mounted Display (HMD) equipped with numerous kinds of sensors, to operate in Mixed Reality (MR) (Milgram and Kishino, 1994), a more generic meaning of AR. The goal is to retrieve information from the external world and to detect and track numerous kinds of objects in real-time. As output, a label will be shown over each recognized object, with its relative name. The entire process focuses on a dynamic system in which both the observer and objects could move in the environment. The real-time constraint implies the need for limiting the adoption of complex detection algorithms (e.g. Convolutional Neural Networks, CNNs) in favor of faster solutions, such as feature detection/matching and tracking algorithms. To avoid possible lack of accuracy while using simpler approaches, the information extracted by complex algorithms is properly exploited to allow faster methods to be more effective. In the following sections, the adopted HMD is presented along with a brief overview of the algorithms exploited by the MR system proposed in this paper.

1.1 Microsoft HoloLens

Microsoft HoloLens (HoloLens,), is an HMD able to project holograms in a real space. It has different kinds of sensors, like RGB and depth cameras and an Inertial Measurement Unit (IMU), that allow a real-time perception of nearby shapes and obstacles. It is provided with two on-board computational units: an Intel 32-bit processor and an Holographic Processing Unit (HPU) that manage both the operating system

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and the real-time update of displayed holograms. This tool is able to determine its relative position with respect to the real world, building in real-time a map of the surrounding environment. Leveraging on its capabilities, who wears this headset is able to move freely in the real space, having the possibility to collect and process different kinds of data that can be displayed directly on the glasses. However, its computational power is limited, and therefore it may not be able to compute costly algorithms in real-time. To this purpose, an external server provided with GPU computational capabilities should be considered. It might be reasonable to adopt Microsoft HoloLens merely as a mixed reality and move the entire computation part to a cloud system. Relying on an external computational system means introducing latency. This means that both HoloLens and the cloud environment should cooperate to reach the right trade-off between accuracy and time complexity, limiting the invocations of the cloud service.

1.2 Object Detection

In the literature, there are several methods to perform object detection from 2D images. One of the most recent and accurate technique derives from the machine learning field (Borji et al., 2015; Han et al., 2018) leveraging on deep Convolutional Neural Networks (CNNs). These kinds of networks result as efficient as complex. Among the possible networks we opted for the fastest and most accurate ones. Three different CNNs are used and compared: *Faster Regional Convolutional Neural (Faster R-CNN)* (Ren et al., 2015), *Region-based Fully Convolutional Networks (R-FCN)* (Dai et al., 2016) and *Single Shot Multibox Detector (SSD)* (Liu et al., 2016). Even if these algorithms are among the fastest in their domain, they require high computational cost to be executed. For this reason (despite the communication delay), it is reasonable to externalize this task to the cloud system.

1.3 Object Tracking

By considering a dynamic environment, the object detection is just the first part of the task. In real-time, a fast methodology to follow the changing position of several objects is needed. The tracking approach computes the newer position of the object by comparing the newer frame to the last one/s (Alper Yilmaz and Shah, 2006). It follows that no latency is admitted in this task and hence the chosen algorithm might have low-complexity to be executed directly by HoloLens. Among the possible choices (Padmavathi S., 2014) for this purpose, the well-known and robust *Mean Shift Tracking* (Wen and Cai, 2006) algorithm is adopted. With an appropriate tracking methodology, the real need to detect a new object is limited to the situation when a new (and unknown) object appears into the Field of View (FoV), making the overall system more rapid and effective.

1.4 Feature Detection and Matching

To catch changes between two images or simply compare two regions, several descriptors that can used. In this specific context, possible objects could appear in the FoV while the tracking algorithm is active. When new objects appear, a new object detection on the image must be requested. One of the most used algorithm for this goal is *Scale Invariant Feature Transform* (*SIFT*) (Lowe, 2004). Unfortunately, this approach is too complex to be executed in HoloLens. For that reason, we opted for the *Oriented FAST Rotated BRIEF* (*ORB*) (Ethan Rublee and Bradski, 2004) algorithm, which is a faster approach with a comparable accuracy in our context.

2 PROPOSED METHOD

In this section, the overall system is analyzed and detailed. The principal goal for this work is to deal with the complexity of the adopted algorithms to succeed in recognizing dynamic objects in the real-time environment. The system is meant to be fast and accurate, leveraging on a high interoperability between the cloud system and the HoloLens system (called local system). The cloud system, provided with high computational resources, is able to perform complex and accurate algorithms in a short period, but suffers from latency due to communication delays. The local system instead is less powerful but can process the video stream in real-time on the HPU. In detail, the HoloLens sensors provide two kinds of information: i) a stream of 2D images and ii) an updated mesh of the observed surface. Furthermore, HoloLens is able to establish the observer's relative position and direction. This data is preprocessed by a *Detection Policy* module that decides what is the lighter action to perform to guarantee the overall object recognition and limit as much as possible complex computations. Depending on the observer's position and gaze direction and the observed scene, that module can activate the *2D-3D Mapping*, the *Object Detection* or the *Object Tracking* modules. Finally, each recognized object is labeled, over-imposing an hologram indicating its name in the real space. Through the entire process, several features are extracted to represent and remind the detected objects. The whole process and all the interactions are exhaustively described in the Sections 2.1 and 2.2.

2.1 Cloud System

The Cloud System performs the object detection task. Due to the complexity of the involved algorithms, it is hosted by a server provided with one of the fastest GPU, the NVIDIA GeForce 1080Ti. The process is described as follows. Firstly, the Local System sends a *Detection Request*, which is an HTTP request containing the last captured frame, to the Cloud System . Then, the picture is processed by the *Object Detection* module that implements the algorithms presented in Section 1.2. For this work we leveraged on pretrained models, freely available on Tensorflow (Tensorflow,), that are *Faster R-CNN* and *R-FCN* with *ResNet 101* and *SSD* with *Inception ResNet V2*. These models are trained on the public dataset COCO (COCO,).
When the Object Detection module processes a new image, a list of Detected Objects (DOs) is returned. Each DO is represented by:

- Bounding Box (BB): the image's rectangle area in which an object is identified. It consists in a couple of coordinates $c_1(x_1, y_1)$, $c_2(x_2, y_2)$, representing the upper-left and bottom-right region corners;
- Class: the most-likely class that the identified object is supposed to belong (e.g. mouse, keyboard, ..);
- Score: the confidence with which the algorithm associates the object to the *Class*. It is defined as $Score = \{x | x \in \Re, x \in [0, 1]\}$

To avoid false detections, we empirically defined a minimum threshold for *Score*. We consider valid detections only DOs having $Score \geq 0.8$.
Finally, the DOs list is returned to the Local System.

2.2 Local System

The Local System runs directly on the HoloLens' hardware. It is developed in C# by using Unity 3D (Unity3D,) and OpenCV (OpenCV,). Unity 3D allows mapping the information coming from the sensors to a virtual environment, in which 1 meter corresponds to a 1 virtual unit. This framework allows to make a representation of the real scene, reconstructing the surfaces and tracking the HoloLens relative position. Furthermore, every virtual object added in the Unity scene, it is displayed as hologram in the real space. The OpenCV framework, instead, is used to perform image processing algorithms over the frames. The system operates in real time, directly on the video stream. According to several variables related to the observed scene and the observer's position, it evaluates whether to perform a detection request or to track the identified objects detected in the past. Furthermore, it performs the 2D-3D and 3D-2D space conversion to map the 2D frame's domain into the 3D space domain (and vice-versa). This mapping is required because HoloLens provides raw data from different sources without mixing them: the video stream is acquired from a 2D RGB camera, while the third spatial dimension is computed from a central depth camera and four gray-scale cameras placed on the headset's frontal sides.
In Fig.1, the local system's flow is shown. From an initial condition, in which the observer is steady, the Local System takes a frame from the *Frame capture* module (Fig.1, A). At startup, when previous knowledge of the surrounding world cannot be exploited, the *Object detection request to server* (Fig.1, G) is triggered to request a new detection to the Cloud System. At this point, the Cloud System starts computing the received frame to extract and provide the right information. Meanwhile the Local System computes, for each acquired frame, a gray-scale histogram, discretized onto 64 bins (this information will be used in a second step). When the Cloud System finishes the computation, it returns a DOs list. The received data (*Receiving detected objects list* module, in Fig.1, B) is used to build the first representation of the observed objects. First of all, it is required to map the 2D detection on the camera's space to the 3D space. This action is performed by the *2D-3D Mapping* module (Fig.1, C) as follows:

1. Defined:
   - $P(x_p, y_p)$, the central pixel of a detected region: it is a position in the frame's space;
   - $C(x_c, y_c, z_c)$, the camera position in the world's space, taken at the same time as the frame is acquired
2. $P(x_p, y_p)$ is transformed from the frame space, to the world space, obtaining $P'(x_p, y_p, z_p)$;
3. A ray (Fig.2), starting from $C(x_c, y_c, z_c)$ and passing through $P'(x_p, y_p, z_p)$, is traced: the intersection between the ray and the environmental mesh identifies a point $I(x_i, y_i, z_i)$, that is an approximation of the object's location in the world space. This step is easily performed by using Unity 3D *Ray Tracing* and *Collider* functionalities.
4. Points 1 to 3 are repeated for each detected region

At each point $I(x_i, y_i, z_i)$ in the world space, the *Labels in Mixed reality* module (Fig.1, D) displays a

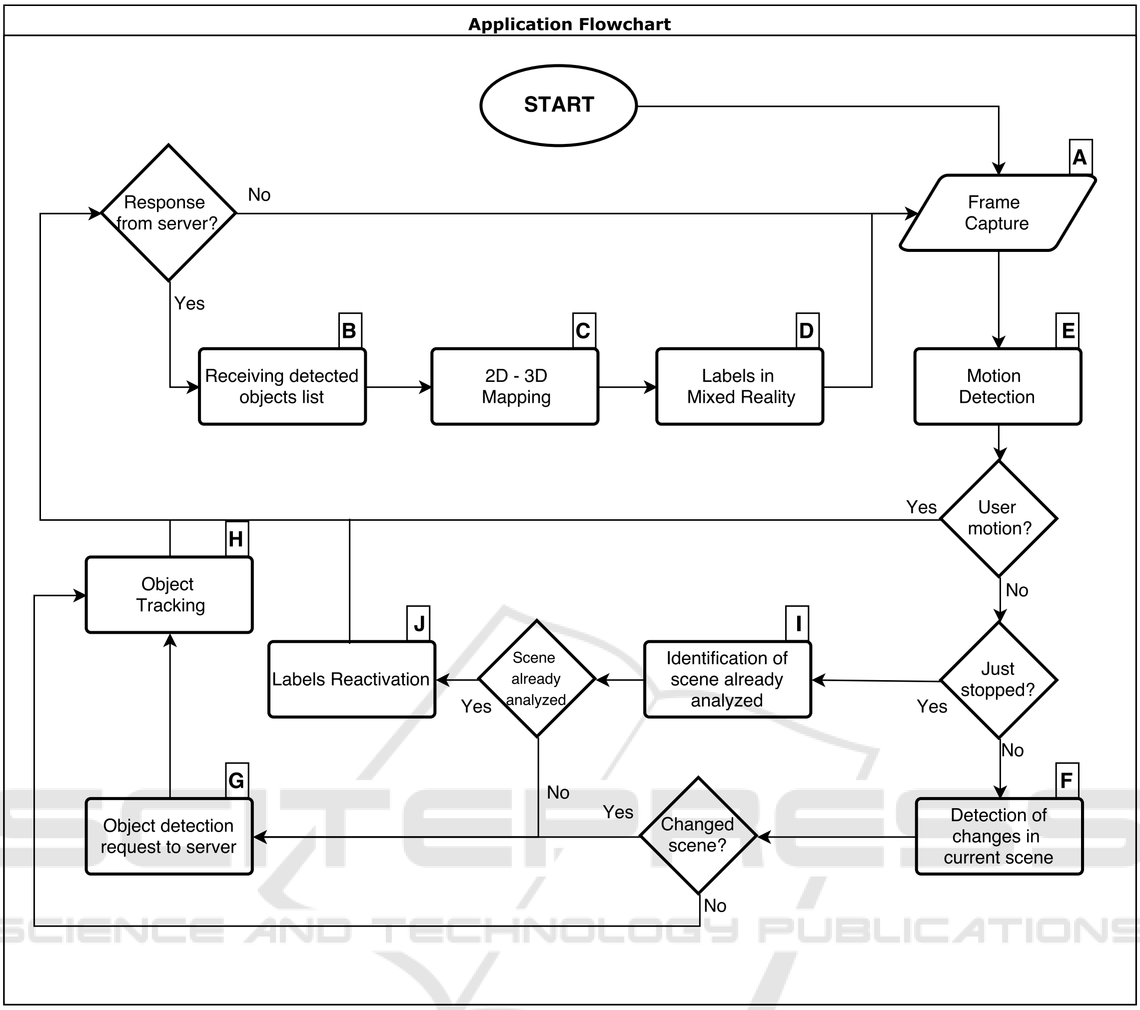


Figure 1: Local System flow diagram.

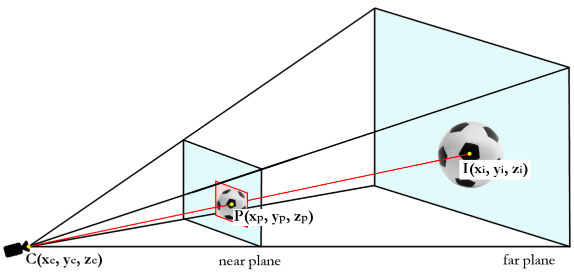


Figure 2: 2D-3D Spatial Mapping.

Unity 3D GameObject *Textmesh* with the respective DO's *Class* as name, as shown in Fig.3. These labels are stored in a vector and are the internal representation of the detected objects. At this step, each object consists in the DO's attributes, plus the coordinate $I(x_i, y_i, z_i)$. For each frame for which a detection is performed, the corresponding *ORB* descriptor is computed: this information represents the frame contents and is stored in memory with the related recognized objects. These data represent the geometric and visual memory of the MR system and are exploited in the following to avoid the analysis of frames corresponding to scenes that are already known. Afterwards, a novel frame is captured and the processing chain behavior depends on several policies and heuristics, the first being based on the observer's state. We define *observer* the user that is wearing the HoloLens and running the application. The observer is free to move into the real world. We assume that the observer is interested in augmenting the scene with DO information only if her/his gaze is quite stable: for that reason, given that the HoloLens camera streams at 30 fps, the Local System is active only under the following conditions:

1. The *Maximum Translation Velocity* (*MTV*) must be lower than 0.27 m/s

2. The *Maximum Angular Velocity* (*MAV*) must be lower than 0.25 rad/s

Overtaking these limits means deactivating the Local System until the values lower again under the respective thresholds. These thresholds are introduced in order to ensure a minimum movement tolerance when the observer is looking at a scene. Both the current translation and angular velocities are available from the gyroscope and accelerometer installed on board the HoloLens: these data are automatically mixed with the ones acquired from the other sensors to determine the relative observer's position and frontal direction.

Every novel frame is processed by the *Detection Policy* module. Starting from an internal representation of previously detected objects, its task is to minimize the effort spent to recognize the objects in the current frame. The possible situations that could occur are summarized as follows:

1. the observer is steady, looking in the same direction and nothing changes in the scene;
2. the observer is steady, looking in the same direction and some object is moving;
3. the observer is steady, looking in the same direction and a new object joins or leaves the scene;
4. the system, due to the observer's movements over the MTV and/or the MAV thresholds, was deactivated and now it is reactivated.

In cases 1, 2, 3 the Detection Policy checks (through the module *"Detection of changes in current scene"* in Fig.1, F) whether there has been any variation in the current scene by comparing the actual frame gray-scale histogram with the previous one. The comparison is done by computing the correlation coefficient d:

$$d(H_1,H_2) = \frac{\sum_I (H_1(I)-\overline{H_1})(H_2(I)-\overline{H_2})}{\sqrt{\sum_I (H_1(I)-\overline{H_1})^2 \sum_I (H_2(I)-\overline{H_2})^2}} \quad (1)$$

where $H_1(I), H_2(I)$ corresponds to the value of the I-th bin for the first and the second histograms,

$$\overline{H_k} = \frac{1}{N}\sum_J H_k(J) \quad (2)$$

and N is the total bins number (in our setting $N = 64$). We empirically defined a threshold $d_{th} = 0.93$. For any $d \leq d_{th}$, we consider that the scene is changed: this means that a new detection is required (Fig.1, G) because case 3 could be happened. In the other cases (1 and 2), a new detection request is avoided and the *Object Tracking* module (Fig.1, H) is activated. The *Object Tracking* module uses the mentioned *Mean Shift Tracking* (MST) algorithm to track a known object in the newly acquire frame. To this end the HSV color space is considered. Then MFT is run using as target the histogram of the H component of the rectangular region determined by the Bounding Box (BB) of each DO. The MST algorithm exploits the same histogram distance measure defined in Equation 1 and determines the new Bounding Box coordinates c_1 and c_2 for each DO. As final step the Object Tracking module updates the DO coordinates in the internal structure and triggers the 2D-3D Spatial Mapping algorithm to update the world point $I(x_i, y_i, z_i)$. This procedure is performed for each DO that was previously detected in the scene. If any object is not detected by the MST algorithm, the module deactivates the labels related to each missed object and will issue a new detection request to the cloud server The 4-th case needs a different treatment by the Detection Policy: the *"Identification of an already analyzed scene"* module (Fig. 1, I) is activated. After the observer has moved, it could look at a new portion of the environment or toward a scene that was already seen and previously analyzed. That module checks this last case by performing a *Geometric Check*, computed as follows:

1. Considering the camera position $C(x_c, y_c, z_c)$ as origin, we define: $\overrightarrow{v_c}$, the unit vector of the observer's looking direction and $\overrightarrow{v_i}$, the unit vector computed from the direction between a stored object position $I(x_i, y_i, z_i)$ and $C(x_c, y_c, z_c)$
2. Compute the cosine of the angle between the two unit vectors: $cos\theta = \overrightarrow{v_i} \cdot \overrightarrow{v_c}$

A minimum threshold $d_{GC} = 0.93$ for the value of $cos\theta$ is empirically defined: this threshold determines whether the observer is looking toward an already recognized object. If none of the objects stored in memory yields $cos\theta \geq d_{GC}$, a new detection request is performed. Otherwise, one must check whether the observed scene has changed from its last representation or not. For this reason, the *ORB* algorithm is used over the whole frame. The key-points computed from the current frame are compared to the ones stored during the last acquisition of the same scene, as shown in Fig.4. Then, a similarity measure s is computed:

$$s = \frac{|\, match \,|}{max(|\, d_1 \,|, |\, d_2 \,|)}, \quad (3)$$

where, $|\, match \,|$ is the number of matching key-points between the two frames and $|\, d_i \,|$ is the number of key-points founded for the i-th descriptor. Also for this measure, a minimum similarity $s_{th} = 0.4$ is defined. If both $cos\theta \geq d_{GC}$ and $s \geq s_{th}$, it might be asserted that the observer is looking at a previous recognized and unchanged scene, otherwise a new detection request

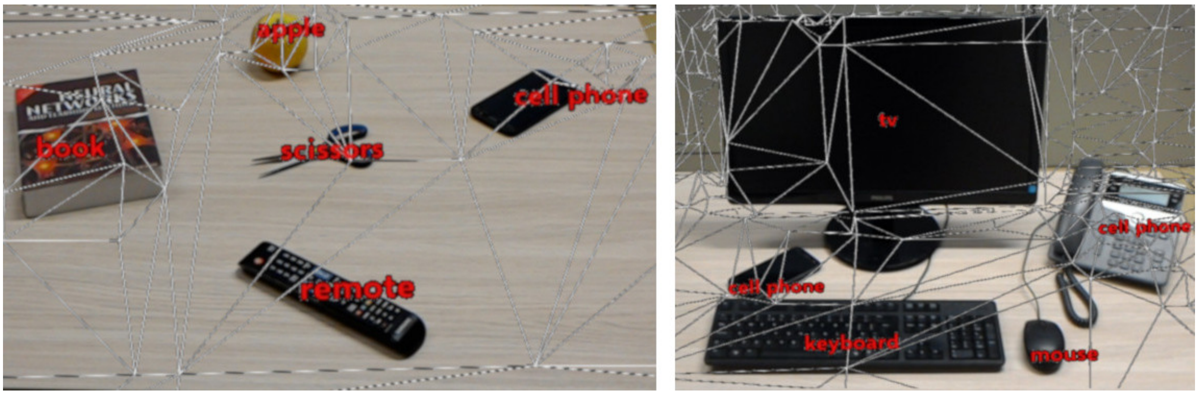


Figure 3: Recognized objects in two different scenes: each *label*, is placed over the respective object. The mesh, retrieved by the sensors and computed by Unity3D, is displayed and wraps the entire visible scene.

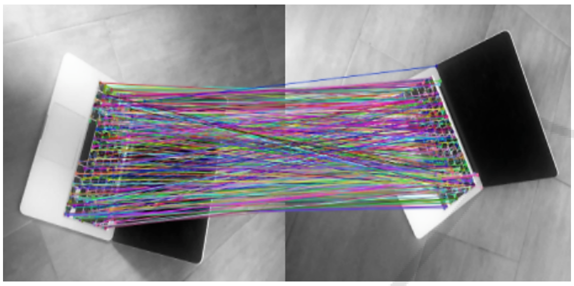


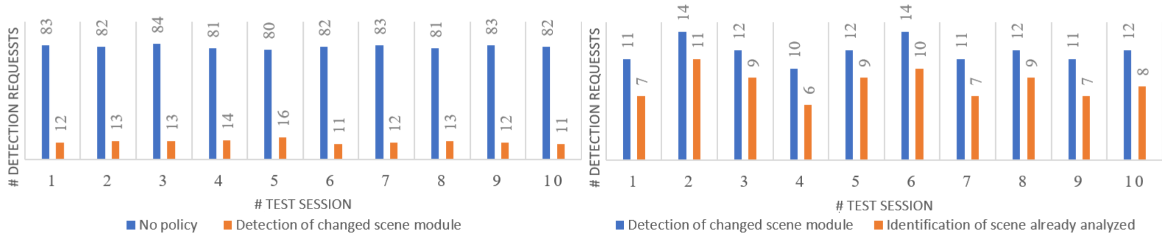
Figure 4: ORB keypoints comparison between two frames.

is needed. In case the check succeeded, a last step must be executed. Supposing that the user is looking to the same scene, but from a different point of view, the bounding boxes position must be recomputed. Referring to the 2D-3D Spatial Mapping and Fig.2, the points $C(x_c, y_c, z_c)$ and $I(x_i, y_i, z_i)$ are known, while $P'(x_p, y_p, z_p)$ must be computed as the intersection between the $\overline{CI}$ segment and the camera's display plane. That point is then translated into the point $P(x_p, y_p)$ in the frame's domain and, as consequence, the coordinates c_1, c_2 are derived. This last step is named 3D-2D Spatial Mapping and is performed by the *Labels Reactivation* module (Fig.1, J) that, after this computation, over-imposes the Unity 3D Textmeshes over the respective recognized objects.

3 EXPERIMENTS AND ANALYSIS

The principal goal for this work is to recognize objects from the real world in real-time. The following experiments have been devised to quantify the gain provided by the designed Detection Policy with respect to a simple reference system relaying solely on cloud frame detection requests. First of all, we determined which algorithm, among the considered detection algorithms, fits better our purposes. We prepared a collection of 50 images about desk items and tech products, each one containing up to five objects. All the objects were selected from the categories that the adopted neural networks were trained to recognize. We tested each CNNs solution in the Cloud System. We setup the cloud service on a local server equipped with an *NVIDIA GeForce 1080 Ti* and connected Hololens through WiFi/LAN networking. This local server clearly simulates an ideal cloud solution with low latency; nonetheless we will show that this is not enough to guarantee real-time operations. Both the *Mean Average Precision* (*mAP*) and the *Execution time* are used as evaluation metrics of the cloud system. The results are the following: (i) *SSD* scored a *mAP* of 24 with an *execution time* of 77 ms; (ii) *R-FCN* scored a *mAP* of 30 with an *execution time* of 127 ms; (iii) *Faster R-CNN* scored a *mAP* of 32 with an *execution time* of 138 ms. On top of that, it must be pointed out that the communication time between Local and Cloud systems is independent from the adopted algorithm: in our settings we measured an average round trip delay of 300 ms for server request and reply. According to the results, we chose *R-FCN* as be the best balance between accuracy and speed. The overall delayed required for a cloud object detection is therefore about 427 ms. Then, the Mean Shift Tracking algorithm is tested to estimate its contribution on the execution time. For a single object, still or moving, a single MST takes on average *43 ms*. For several objects in the same picture, the time complexity raises linearly with the number of objects. To deal with this problem, the MST has been implemented in a parallel fashion so as to manage 5 concurrent tracking threads: it means that up to 5 objects can be tracked at the same time.

In Table 1, the main execution times for all the policies and heuristics used in our systems are shown.



(a) (b)

Figure 5: (a.) Detection requests reduction related to the "Detection of changes in current scene" (Fig.1, F) module; (b.) Detection requests reduction related to the "Identification of scene already analyzed" (Fig.1, I) module.

The obtained results show that the "Motion detection" and the "Detection of changes in the current scene" modules are quite fast; the slower mechanism is represented by the module "Identification of an already analyzed scene", that in any case introduces a latency of about 243 ms that is much better than the cloud system delay that is approximately 427 ms. The ORB algorithm is performed both in this module and after every detection request: even if performing this action is time-costly, the retrieved information could avoid a new detection request every time the observer looks again to an already seen location. To test the impact of the different checks and policies, a scene with 5 objects has been set up. The evaluation consisted in two different tests, repeated ten times, each one by a different user.

The first test is related to the "Detection of changes in the current scene" module. Standing still, in front of the scene, the number of cloud detection requests performed in 60 seconds is logged. As a reference system we consider the case when we disable all the designed policies, i.e. a new cloud detection request is issued as soon as a reply from the previous one is received. Then, we repeat the same experiment a second time by activating the "Detection of changes" module. The results shown in Fig.5.a confirm that the designed heuristic yields a significant reduction of detection requests that lower from 82 requests per minute (rpm) to an average of 13 rpm in the second case.

A second test is performed on the "Identification of an already analyzed scene" module: in this case, another similar scene with 5 objects was prepared. After a first detection of the new test environment, each tester gazed alternatively 10 times the two scenes. The comparison is evaluated on the sent requests, having just the "Detection of changes" module activated. The results provide in Fig.5.b show further improvement of the proposed technique. All the users experimenting the proposed MR system confirmed the beneficial effect of the designed heuristics: in particular, during the experiments, the users did not evidence a wrong or badly aligned MR labels. More importantly the 10 users confirmed that the system works in real-time with labels correctly refreshed. According to the previous results, the Local System plays an important role in limiting the number of detection requests: both MST and Detection Policy algorithms perform faster than the delay induced by the communication between Local and Cloud systems. These modules improve significantly the performance and the responsiveness of the application. In the best case, in which the observer is statically looking at a scene, the Local System can process up to about 18 fps by the activation of MST and the "Detection of changes for current scene" module: this is a significant improvement compared with the limit of 1.5 fps imposed by a simple use of cloud detection only.

Table 1: Execution time for checks and policy modules.

Module	Exec. time
Motion detection: MTV and MAV computation	< 1 ms
Detection of changes in the current scene: Frame's gray-scale histogram	13 ms
Ident. of already analyzed scene : Geometric Check ORB computation Similarity measure (ORB key-points)	< 1 ms 197 ms 46 ms

4 CONCLUSIONS

This paper presented a mixed reality system, able to detect and track generic objects in a dynamic environment in real-time. That system dealt with complexity problems of detection algorithms and limited computational resources by combining the HoloLens' processor with a cloud system equipped with high computational capabilities. The Cloud System was in charge to process R-FCN algorithm to detect objects from a frame with the right compromise between speed and accuracy. HoloLens runs the Local System, which performs objects tracking, features extraction and spatial mapping tasks. Several policies and heuristics are introduced in the Local System in order to limit the detection requests to the Cloud System. Limiting the external requests implied an increment of about 12 times the total frames per second processed (in the best case), without altering the overall system's accuracy.

REFERENCES

Alper Yilmaz, O. J. and Shah, M. (2006). Object Tracking: A Survey.

Azuma, R. T. (1997). A survey of augmented reality. *Presence: Teleoperators and virtual environments*, 6(4):355–385.

Borji, A., Cheng, M.-M., Jiang, H., and Li, J. (2015). Salient object detection: A benchmark. *IEEE transactions on image processing*, 24(12):5706–5722.

COCO. http://cocodataset.org/.

Dai, J., Li, Y., He, K., and Sun, J. (2016). R-fcn: Object detection via region-based fully convolutional networks. In *Advances in neural information processing systems*, pages 379–387.

Ethan Rublee, Vincent Rabaud, K. K. and Bradski, G. (2004). Orb: an efficient alternative to sift or surf.

Han, J., Zhang, D., Cheng, G., Liu, N., and Xu, D. (2018). Advanced deep-learning techniques for salient and category-specific object detection: a survey. *IEEE Signal Processing Magazine*, 35(1):84–100.

HoloLens, M. *https://www.microsoft.com/hololens*.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., and Berg, A. C. (2016). Ssd: Single shot multibox detector. In *European conference on computer vision*, pages 21–37. Springer.

Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints.

Milgram, P. and Kishino, F. (1994). A taxonomy of mixed reality visual displays.

OpenCV. https://opencv.org//.

Padmavathi S., D. S. (2014). Survey on tracking algorithms. *International Journal of Engineering Research and Technology (IJERT)*.

Ren, S., He, K., Girshick, R., and Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pages 91–99.

Tensorflow. https://www.tensorflow.org/.

Unity3D. https://unity3d.com/.

Wen, Z.-Q. and Cai, Z.-X. (2006). Mean shift algorithm and its application in tracking of objects. In *Machine Learning and Cybernetics, 2006 International Conference on*, pages 4024–4028. IEEE.