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Experimental technique to enhance SLAM modelling of autonomous vehicle with Microsoft© Hololens

MOEZZI Reza[1,2,a], HLAVA Jaroslav[2,b], KRČMAŘÍK David[1,c] and KOČÍ Jan[1,d]

[1] Institute for Nanomaterials, Advanced Technologies and Innovation, Technical University of Liberec, Studentská 2, 461 17, Liberec, Czech Republic

[2] Faculty of Mechatronics, Informatics and Interdisciplinary Studies, Technical University of Liberec, Studentská 2, 461 17, Liberec, Czech Republic

[a]reza.moezzi@tul.cz, [b]jaroslav.hlava@tul.cz, [c]david.krcmarik@tul.cz, [d]jan.koci@tul.cz

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Abstract. This presented paper, intends to introduce new approach to Simultaneous Localization and Mapping (SLAM) problem in autonomous vehicle by scanning the environment based on commercially available Microsoft HoloLens technology. Such a device is the first functional augmented reality gadget offered to a wide audiences. The whole mean of project is to propose an innovative hybrid architecture on SLAM. For certain landmarks extended Kalman filter (EKF) is applied. Therefore the computational complexity is minimized and remaining information for absolute reliable and accurate locations are achieved.

Introduction

In order to navigate an autonomous robot in indefinite environment, localization is necessary to know where the robot is. Localization is the estimation of robot position based on a definite map of environment. Contrarywise, mapping is the structure of environment's map, knowing the right pathway of the robot. [1] in an indefinite environment for autonomous robot, SLAM (Simultaneous Localization and Mapping) model is essential for navigation [2].

The Extended Kalman Filter (EKF) was generally implemented in the SLAM modelling for decades [3]. In mapping structure, map involves the categorizations of landmarks, which each one, characterizes the position of a barrier or a part of the barrier. New different approaches to SLAM have been developed during recent years [4]. FastSLAM is introduced by Montemerlo & Thruns [5] for stochastic SLAM. In this algorithm, the state variables are divided into two different sets, first is evaluated using particle filtering and second valued with EKF. FastSLAM significantly diminishes the problem sophistication [6]. Another approach is called L-SLAM [7] focused on orientation of each particle rather than fastSLAM, which models the orientation along the robot's position. In all methods, landmarks are fully covariant with each other and cause a quadric computational complexity according to their number in the map [8].

On the other hand, in AR (augmented reality) field, Spatial mapping feature in Micrrosft© holoLens delivers a detailed image of real-world surfaces in the environment around it (Fig 1). So, in this experimental project, we will preserve the map with the comparative locations of the landmarks and the corresponding path provided by HoloLens spatial mapping, and only a minor number of the landmarks are active in each EKF step. Therefore, the computational time and cost decreas and the absolute locations of the landmarks would be derived more reliable and accurate.

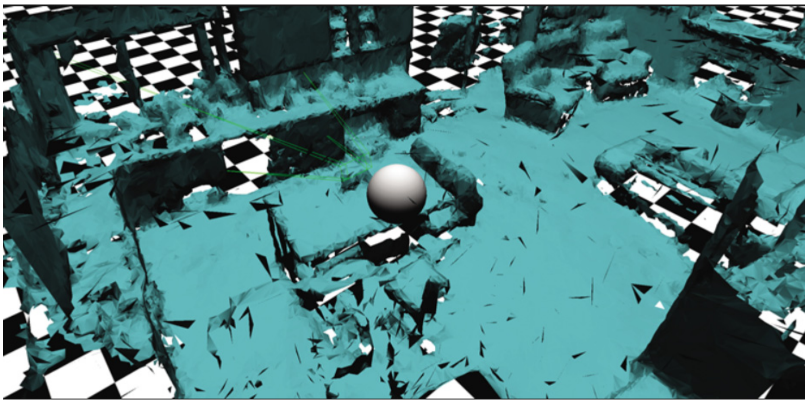

Fig. 1: 3D mapping by Microsoft© HoloLens

SLAM

The simultaneous localization and mapping problem is generally abbreviated as SLAM, define when the robot does not know its orientation and location, and also the map of environment is not accessible. In its place, control actions $u_{1:t}$ and measurements $z_{1:t}$ is given. The term "simultaneous localization and mapping" describes the follow-on problem: In SLAM, the vehicle obtains a map of its environment whereas simultaneously localize itself according to the map [9]. The complete SLAM problem would be defined in form of a probability distribution function. If the initial state of the vehicle x_0^R (state at t=0) and landmark observations Z_t and control inputs U_t up to and including time t are available, the joint posterior density of the landmark's locations and the state of the autonomous robot can be explained by the following probability distribution function:

$$P(x_t^R, m|Z_t, U_t, X_0^R) \tag{1}$$

If the state of the motion of the robot x_t^R , and the right locations of the landmarks **m** are given, the observation model describes the probability of seeing of all landmarks z_t, Consequently, we can state the sensing of the vehicle in probabilistic form [10]. For easiness, the motion of the robot and map of landmarks at time step t are noted as x_t in form of following augmented set [11] and it will be denoted as state of the whole system and the probabilistic observation model:

$$x_k = \{x_k^R, m\} \text{ (State of entire system)} \tag{2}$$

$$P(z_t|x_t) \text{ (observation model)} \tag{3}$$

An autonomous vehicle accomplishes actions in the environment that varies the position of it. This action is due to the order of control actions. If u_t is defined as control action, then $U_t = \{u_1, u_2, \ldots, u_t\}$ would be the set of actions performed by the robot at time t, transition density below expresses the way the location of the robot changes probabilistically:

$$P(x_t|x_{t-1}, u_t) \tag{4}$$

Above transition probability density acknowledge us that if at time step t-1 the vehicle was located at x_{t-1}, and performed a control action u_t, then it will stand at location x_t, at time step t. Mentioned transaction density is then motion model which defines how the control action u_t alters the location of the vehicle. SLAM can be described as a Bayesian estimation problem [10]. Therefore, location of the vehicle and landmark can be estimated with the consideration of disturbances. Regarding to probabilistic aspect, it can be said that the vehicle has a **belief** of where its pose and landmark position is. then the vehicle is not seeing one specific location but several positions for landmarks and itself at time t.

The **belief** of vehicle could be explained by a probability density total locations $x_t \in S$ where S is the set of all positions of the landmarks and the vehicle. The following formula states the belief of vehicle:

$$Bel(x_t) = P(x_t|X_{t-1}, U_t, x_0) \tag{5}$$

That is, with the reflection that the map of landmarks is m, the robot believes that it is at state x_t^R at time t, specified the initial state x_0 and all locations of the robot x_0^R, and the set of control actions U_t up to time t. This probability distribution function shows the maximum probability at which the whole system could be. The final goal of SLAM is to deliver this belief as adjacent as possible to the real system's distribution. There is only one maximum point out of this function at the true locations and elsewhere is zero. This description defines the unimodal system. Using total probability and the Markov localization [12] gives us an efficient formula for the next step as following.

$$Bel(x_t) = P(x_t|z_1, u_0, z_2, u_1, \dots, z_{t-1}, u_t, x_0) = \int_S P(x_t|x_{t-1}, Z_{t-1}, U_t, x_0) \times P(x_{t-1}|Z_{t-1}, U_t, x_0)\, dx_{t-1} \tag{6}$$

Markov assumption says that the prior state of the system is independent of the present state based on information of the present state. this assumption can be used, and It makes the problem simpler [9].

EKF SLAM

An explanation to the SLAM using EKF, with various motivating theoretical explanation, is comprehensively described in [9] . This algorithm is performed on autonomous vehicle, regardless of the recently reported variation of its estimation because it is an empirical for the nonlinear filtering problem. Gaussian noise assumption describes the EKF which expressively weakens the EKF SLAM's capability to deal with uncertainty. With a great uncertainty in the posterior, the linearization in the EKF sometime miscarries. Therefore, an extra hybrid model combined with Bayes filter EKF based, is demanded. the procedure has two steps, first prediction and second update to solve SLAM using the measured Lidar sensor data of the mobile vehicle. Figure 3 illustrates the result of simulation of EKF SLAM algorithm in Matlab based on webmap data collected with Lidar scanner.

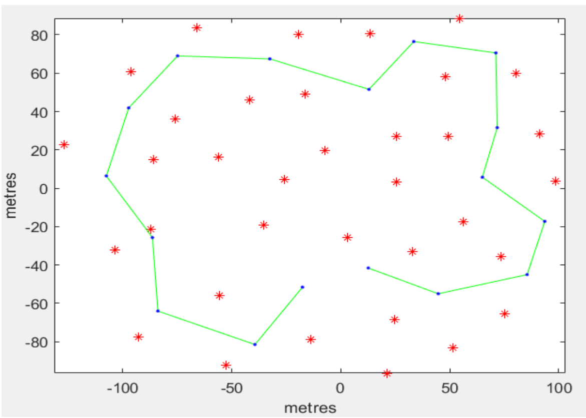

Fig. 2: EKF SLAM algorithm simulation result in Matlab

Mapping with HoloLens

HoloLens [13] with spatial mapping feature, is capable to map scene of its surrounding environment. The device performs mapping by scanning in a 70-degree cone type region between 0.8 and 3.3 m from it and sketch a mesh on what it observes. Spatial mapping is able to detect environmental objects like walls, ceiling, chairs, floor, tables and the collected information can be used to put objects in correct places (figure 3). The main purposes of this feature are holograms navigation, physics of object, occlusion, placement and visualization. Continuous mapping possibility is best suited for dynamic environments where user needs to react to the environment. Only disadvantage of continuous scanning is that it has higher CPU impact and consequently, it affects performance and heats up the device.

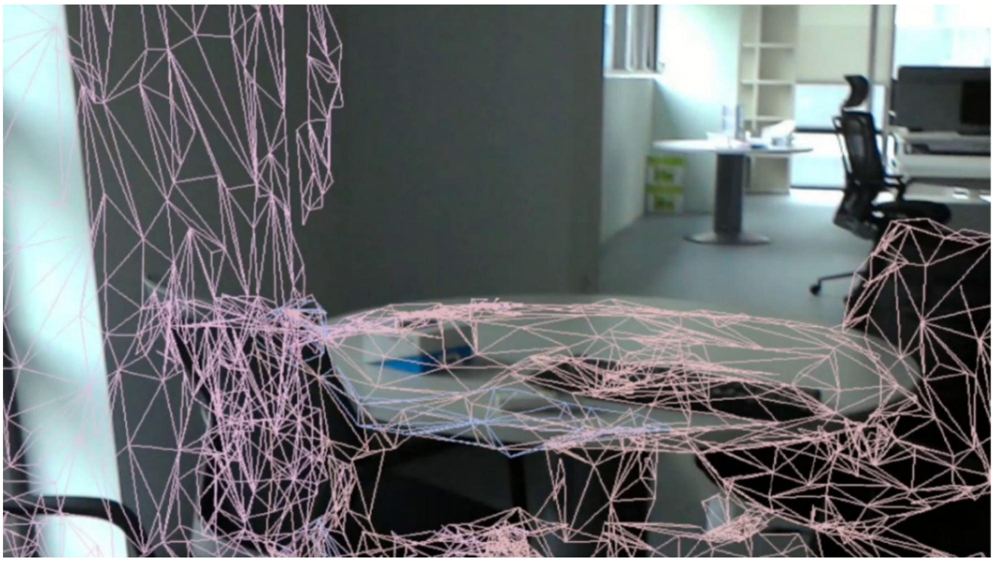

Fig. 3: Spatial Mapping with HoloLens in indoor environment

In mapping of environment, HoloLens applies three steps by programmed scripts, first Spatial Processing Test class allows application to scan the environment for a specified amount of time and then process the Spatial Mapping Mesh (find planes, remove vertices) after defined time has expired, this step prepare the device for mapping in a certain time.

```
public class SpatialProcessingTest : Singleton<SpatialProcessingTest>
{
    [Tooltip("How much time (in seconds) that the SurfaceObserver will run after being started; used when 'Limit Scanning By Time' is checked."
    public float scanTime = 30.0f;

    [Tooltip("Material to use when rendering Spatial Mapping meshes while the observer is running.")]
    public Material defaultMaterial;

    [Tooltip("Optional Material to use when rendering Spatial Mapping meshes after the observer has been stopped.")]
    public Material secondaryMaterial;

    [Tooltip("Minimum number of floor planes required in order to exit scanning/processing mode.")]
    public uint minimumFloors = 1;
```

Fig. 4: First step in HoloLens mapping, Spatial processing test class

The second step is Remove Surface Vertices which will remove any vertices from the Spatial Mapping Mesh that fall within the bounding volume. This can be implemented to create holes in the environment, or to help reduce triangle count after finding planes.

```
public class RemoveSurfaceVertices : Singleton<RemoveSurfaceVertices>
{
    [Tooltip("The amount, if any, to expand each bounding volume by.")]
    public float BoundsExpansion = 0.0f;


    /// <param name="source"></param>
    /// <param name="args"></param>
    public delegate void EventHandler(object source, EventArgs args);

    public event EventHandler RemoveVerticesComplete;

    private bool removingVerts = false;

    private Queue<Bounds> boundingObjectsQueue;

#if UNITY_EDITOR || UNITY_STANDALONE

    private static readonly float FrameTime = .016f;
```

Fig. 5: Second step in HoloLens mapping, Remove surface vertices

And the final step is Surface Meshes to Planes class that will find and create planes based on the meshes returned by the Spatial Mapping Manager's Observer. This class calls a sub class named Plane Types Enum Editor which enables multi-selection of the 'Draw Planes' and 'Destroy Planes' options in the Inspector.

```
public class PlaneTypesEnumEditor : Editor
{
    public SerializedProperty drawPlanesMask;
    public SerializedProperty destroyPlanesMask;

    void OnEnable()
    {
        drawPlanesMask = serializedObject.FindProperty("drawPlanesMask");
        destroyPlanesMask = serializedObject.FindProperty("destroyPlanesMask");
    }

    public override void OnInspectorGUI()
    {
        base.OnInspectorGUI();
        serializedObject.Update();

        drawPlanesMask.intValue = (int)((PlaneTypes)EditorGUILayout.EnumMaskField
                ("Draw Planes", (PlaneTypes)drawPlanesMask.intValue));

        destroyPlanesMask.intValue = (int)((PlaneTypes)EditorGUILayout.EnumMaskField
                ("Destroy Planes", (PlaneTypes)destroyPlanesMask.intValue));

        serializedObject.ApplyModifiedProperties();
    }
}
```

Fig. 6: Third step in HoloLens mapping uses plane type enum editor class

Enhanced SLAM Algorithm

An enhanced hybrid SLAM with EKF has been considered here, improved by HoloLens mapping data which acting as a spectator to acquire the on-line system uncertainty. An adaptive state estimation technique using EKF and HoloLens has been developed. In this study, the mobile vehicle with encoder values (w_{rk} ,w_{lk}) is learned using mapping Hololens data in the update-step. The mean μ_t and covariance matrix $\sum_t$, which are derived from environmental information values (x_t, y_t, θ_t) using the spatial mapping algorithm, is entered to the prediction-step, as illustrated in Figure 7.

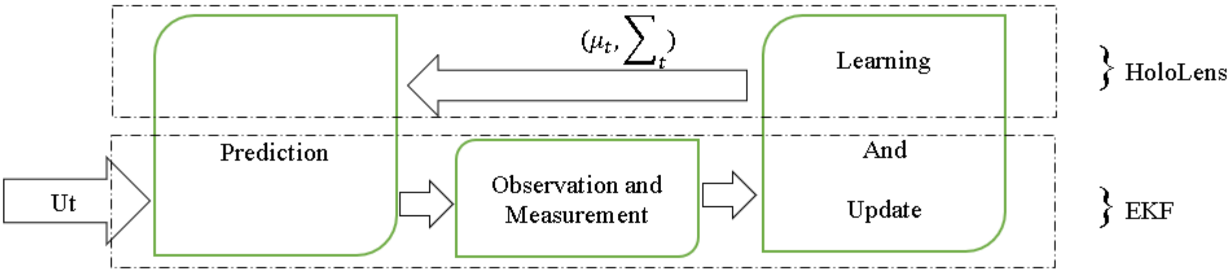

Fig. 7: The diagram of EKF and HoloLens Hybrid SLAM

Spatial mapping data particularly is very useful on measurement and observation step because it decreases calculation time. If the vehicle remains on a prediction step, it comprises all input information which may include unnecessary data. However, the combined algorithm helps to learn about only the necessary data through observation step. Through this technique, the calculation time get decreased based on less complicated problem definition and fewer iterations.

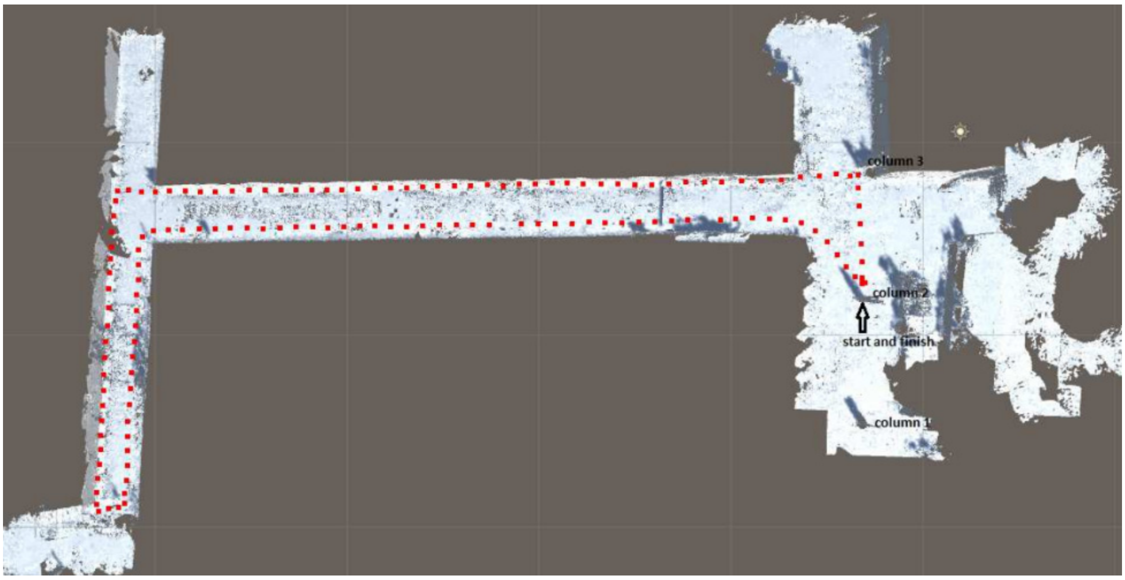

Fig. 8: Map aquired by autonomous robot in indefinite environment

Future work

According to this tremendous approach, we have reached interesting results which can be improved. To control vehicle in lateral path, fuzzy logic can be implemented for routing [14] of the Autonomous vehicle. Also, we can merge our approach with PID controller [15] based on the localization method to increase the accuracy. The camera of HoloLens can storage images of mapping to classify the most security routing using image processing tools described in [16]. The theoretical and experimental studies [17] in the field of fibre networks are rapidly increasing and there is room to carry out in autonomous vehicle. Our future work might be focus on the numerical model [18] of the Autonomous vehicle [19].

Conclusion

The SLAM is very interesting and essential problem in the field of autonomous mobile vehicle while it navigates desired path and simultaneously creating a map of the physical environment and the vehicle estimates position of itself on corresponding map. This paper illustrated an enhanced hybrid SLAM method which combines augmented reality device on a mobile robot, to minimize the EKF SLAM error which mostly caused by its linearization procedure and disturbance assumption. This algorithm, as writers have discovered, is the first innovative approach in SLAM problem which applies augmented reality capabilities. The simulation results of EKF SLAM is shown, the HoloLens classes for mapping are studied and the experimental result of hybrid mapping architecture is obtained.

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