Towards reconstruction of human trajectories in indoor environments

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Abstract. In this paper, we propose to study how to reconstruct the human trajectory in complex environments (indoor) such as museums that are often not equipped with WIFI or other monitoring techniques. We have set up a micro-localization infrastructure Bluetooth Low Energy. We propose to use a sampling method for finding position stops (point in a trajectory), because a deep learning method is not adapted to this case.

Keywords: trajectory · micro-localization · sampling.

1 Introduction

The reconstruction of human trajectories in indoor environments is a major challenge for complex museums who want to know which are the most visited rooms or how long visitors stay in front of a work. This work also aims to contribute to the dynamic adaptation of scenarios such as interactions between a human and a robot (Nao) by providing information like spatio-temporal sequences [4]. In outdoor, the reconstruction of trajectories is facilitated by the use of GPS, but in indoor the GPS does not work and on the other hand most museums do not have WIFI. We have endeavored to reconstruct human trajectories using a device based on Bluetooth Low Energy (BLE) and more specifically the use of the iBeacon protocol. In the rest of the paper, we present micro-localization techniques for indoor environment before moving to the identification of visitor stops. Then we discuss experimentation that allowed to validate the principle of discretization by sampling. Finally we will conclude by giving some perspectives to this work.

2 Micro-localization techniques for indoor environments

2.1 Bluetooth signal

We choose to use badges (credit card size) that have a BLE chip that emits the iBeacon protocol. The people you want to follow are wearing this badge. The iBeacon protocol makes it possible to recover the Bluetooth signal strength (RSSI in dB) without the need for pairing between the signal transmitter and the receiver [2, 3].

2.2 Technical architecture for collecting Bluetooth signal

Fig. 1 shows the architecture composed of collectors (Raspberry PI3 micro-computer) that are positioned in a building. They detect in real time badges nearby and record the power they capture (RSSI signal). The values are stored in a MongoDB database (via FileBeats and Logstash). Data are analyzed in real time by an algorithm in Python that calculates visitor stops and trajectories.

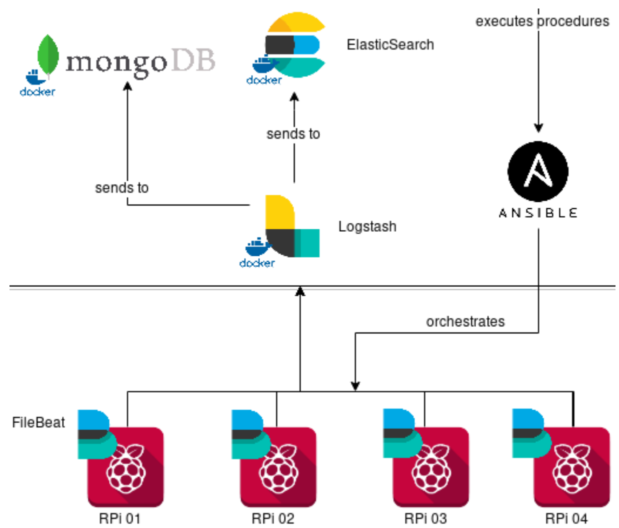

Fig. 1. Technical architecture for collecting Bluetooth signal.

3 Identification of visitor stops

Identifying visitor stops is the first step in rebuilding the trajectory of people. So we set out to set up an algorithm for identifying stops based on a temporal sampling (1s, 2s and 5s). The collector returning the highest average of the RSSI collected on a sample is considered as a stopping position. A sub-sampling, with the values of RSSI allows to extract a position in most cases. A first software was created to propose positions by badge. Given the weaknesses of the localization signal intensity [1], the solution generates intermediate positions, when there is an ambiguity. For two signals picked up during a time undergoing the same variations, with an almost identical power average, it is not possible to determine whether the badge is closer to either of the collectors. Preliminary results suggest that the value of the RSSI depends on many environmental parameters: humidity levels in the air, movements of the human body, positioning relative to the collection device and presence of aqueous medium between the beacon and the badges. In fact, the badge wearer can be one meter from the collector A, and fifteen meters from the collector B. The identical intensities can be related to the environment: the badge wearer is with someone who is positioned between his badge and the collector, while nothing blocks the signal of the badge to the collector B. The classification of the human position could have been based on in-depth learning techniques and on-the-ground truth. These signal propagation problems prevent us from using these AI methods.

4 Experimentation

We conducted experiments to collect positions and initiate experimental work to determine a sampling value. The two figures below are from the same experiment with two different sampling values. The sampling is done in soon after the collection using an algorithm written in Python. Fig. 2 shows the result with a sampling at 1 second and Fig. 3 at 5 seconds. All that has been done so far has only one goal: to highlight the movements of visitors by locating their stops in front of collection devices. A lot of visualization is achievable with Kibana. Only the value of captured power (RSSI) by badge and by collection device interests us: we simply want to know if in a temporal graph, these stops are remarkable. One-second sampling shows the effect of noise on the signal: variations are important.

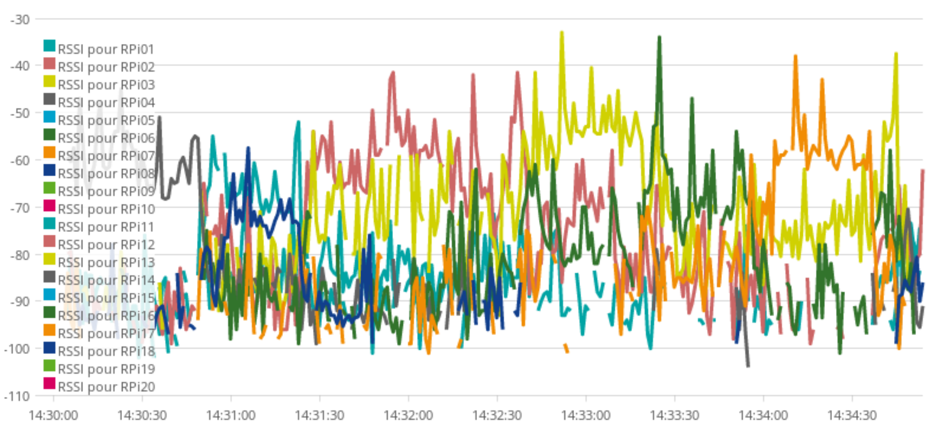

Fig. 2. One-second sampling.

Despite significant variations in intensity received, stops in front of collection devices are obvious. The intensity picked up near these sensors is higher than elsewhere. It forms peaks over several seconds, where the intensity is higher. These intensities apply for a single badge. By quickly analyzing this graph, we can identify the path of the badge in front of the devices: firstly number 14 (gray), then 11 (turquoise), 12 (red), 13 (light green), 16 (green), and 17 (orange).

After a five-second sampling, the impact of the variations is much smaller. The stops are much better highlighted.

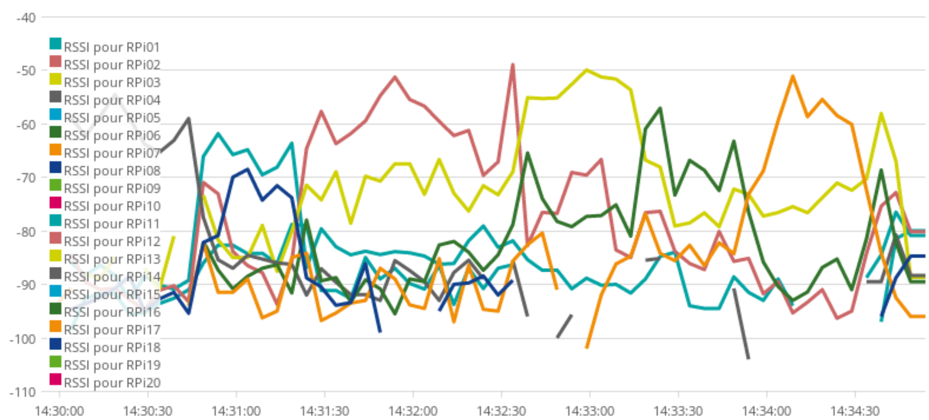

Fig. 3. Five-second sampling.

5 Conclusion and future works

To conclude we propose an infrastructure for collecting human position in indoor environments. A technology based on Bluetooth Low Energy (iBeacon) was chosen, this one is coupled with an ElasticSearch infrastructure. To determine human position stops, we use a discretization method focusing mainly on the average values collected for a temporal sampling. In future works, we would trying to use a graph of possible location in order to improve our algorithm and remove ambiguities.

References

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