Inertial-based smart indoor localisation system

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ABSTRACT

The location-aware technologies are crucial for cyber physical applications. In this contribution, a smart indoor localisation system is proposed: it is able to recognise and track user activities, given the initial pose. The key idea is the well-known prediction-correction approach used in field robotics. To this end, a rough estimate of the user position is formed by exploiting proprioceptive sensors (e.g., inertial measurement unit), thereafter it is refined by data collected from the smart environment (e.g., radio frequency systems).

Keywords

Indoor Localisation, Inertial Measurement Unit, Model-based Localisation

1. INTRODUCTION

Indoor Localisation System (ILS) technology is considered a pillar in the development of cyber physical systems. It brings, indeed, the power of GPS in indoor environment, where people spend most of their time. Therefore it is not surprising that indoor positioning has become a focus for research and development during the past decade. Moreover it represents also a strategic asset considering special population care, key building management, retail industry, personal service, and rescue applications.

Despite its importance, no general solution for indoor localisation based on a single technology, such as that provided outdoors by satellite-based navigation, has been provided: the proposed solutions are far away from achieving indoor positioning with an accuracy of 1 m. Most of the current systems are based on dedicated local infrastructure and/or customised mobile units. Several approaches are based on radio frequency antenna using fingerprinting ora ranging techniques. Recently, also Micro Electro Mechanical Systems (MEMS) sensors, compass, accelerometer, gyroscope and barometer have been gradually integrated into Inertial Measurement Unit (IMU) and embedded in personal devices, which can be used to provide and assist the user indoor positioning and tracking.

In this paper, a waist-mounted IMU is used to produce the position estimate of a user; this estimate is further refined by fusing data collected from a smart environment. Data from sensors are fused using a Bayesian filter, according to the well-known prediction correction schema adopted in field robotics. The main achievement is represented by a good trade-off between the computational complexity of the procedure and the accuracy of the results.

2. SMART INDOOR LOCALISATION SYSTEM

The indoor localisation system is composed by 9DoF IMU (tri-axial gyroscope, tri-axial accelerometer, tri-axial magnetometer), a computation unit and radio frequency devices. The user is equipped with an IMU, a radio frequency (RF) receiver (a Bluetooth/Wi-Fi antenna or RFID reader), and a computation unit (a tablet or a laptop); the radio frequency devices (Bluetooth/Wi-Fi antenna or RFID tags) are deployed in the environment in known positions with respect to a global reference frame.

The IMU is waist mounted: specifically a MEMS IMU of a smartphone is placed near the center of gravity of the user, as shown in Fig. 1. In this way, the reference frame attached to the user allows to easily compute the heading (rotation along V-axis) and the vertical acceleration a_V, used to classify the human activities.

Knowing the initial position of the user in the global reference frame, a model-based prediction-correction Bayesian filter is developed to estimate the pose of the user. The vector to be estimated is $p_k = [\mathbf{x}_k^T \theta_k]^T$, where $\mathbf{x}_k = [x_k, y_k, z_k]^T$ represents the position of the user with respect to a global

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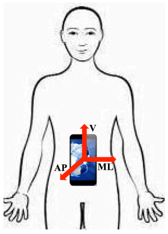

Figure 1: IMU reference frame: the z-axis points to the vertical axis, the x-axis to the antero-posterior, and the y-axis to the medio-lateral

3D Cartesian reference frame and θ_k is the heading. In the following, the z axis of the global reference frame points in the vertical direction, while the (x, y)–plane represents the ground floor of the environment.

In the prediction step, the heading is updated using data from gyroscopes corrected by magnetometer and accelerometer measurements, as in [3, 4]. The position estimate is computed as

$$\mathbf{x}_k = \mathbf{x}_{k-1} + f(\Delta s_{A,k}, \Delta\theta_k) \tag{1}$$

where $\Delta\theta_k$ and $\Delta s_{A,k}$ are the rotation and the displacement of the user during the time interval $[k-1, \ldots, k)$, respectively. It is worth noticing that the displacement $\Delta s_{A,k}$ depends on the human activity detected. Here, only three activities are considered: *Staying Still*, *Taking Lift*, and *Walking*. The human activities are classified by means of a decision tree analysing the vertical acceleration provided by the IMU, as suggested in [1, 2]. The finite state machine that describes the possible state transitions is depicted in Fig. 2. During *Staying Still* $\Delta s_{A,k} = 0$, since no motion occurs and the position coordinates do not change. *Taking Lift* updates only the z_k coordinate according to the following equations

$$\begin{array}{rcl} z_k & = & z_{k-1} + v_{z,k-1}\Delta t_k + \frac{1}{2} a_{V,k}\Delta t_k^2 \\ v_k & = & v_{k01} + a_{V,k}\Delta t_k \end{array} \tag{2}$$

where v_k is the vertical velocity. During *Walking*, only motion in the (x, y)–plane occurs and the vertical acceleration from IMU is used to compute the displacement, as explained in [5]

$$\Delta s_A = \beta \sqrt[4]{a_{V,M} - a_{V,m}} \tag{3}$$

where β is a parameter depending on the user, $a_{V,M}$ and $a_{V,m}$ are the maximum and minimum vertical acceleration during a step event, respectively. The state transition model is composed by the following equations

$$\begin{array}{rcl} x_k & = & x_{k-1} + \Delta s_{A,k} \cos\theta_k \\ y_k & = & y_{k-1} + \Delta s_{A,k} \sin\theta_k . \end{array} \tag{4}$$

Unfortunately, the inertial sensors are affected by drift: to partially alleviate this issue and improve the reliability of the system, the measurements from the RF devices are exploited. Specifically we suppose that the position, the heading and the coverage of the RF devices are known: once the computation unit identifies the perceived device, it is able to reset its estimate and to reduce the estimation error. The error, indeed, is be bounded by the maximum range of the antenna, so if short-range antenna (RFID tags or Bluetooth) is considered, the quality of the estimate is significantly refined.

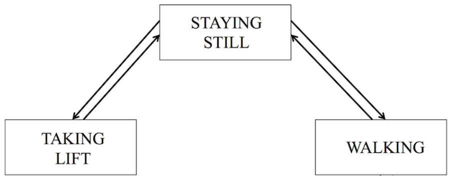

Figure 2: Human activities

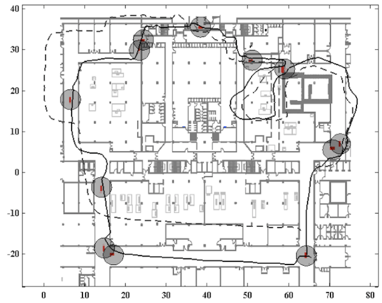

Figure 3: Indoor results in a complex indoor environment: IMU path (dashed line), smart localisation system (solid line), tags (red square), main radiation lobe (grey circles)

3. EXPERIMENTAL RESULTS

The results obtained by the proposed smart localisation system are reported in Fig. 3. During the experiment, the user walks in a complex indoor environment, equipped with a waist worn IMU (MPU9150 from Invensense) connected to a laptop via Bluetooth and a CAEN RFID reader connected to the same laptop via high speed USB. In the environment 12 RFID tags from Omni-ID are deployed. The user executes 500 steps, covering a distance of up to 300 m and having several resting periods. In Fig. 3 the position estimated using the IMU and the one obtained applying the correction of the smart environment are compared.

4. REFERENCES

[1] De Cillis, F., De Simio, F., Faramondi, L., Inderst, F., Pascucci, F., Setola, R., Indoor Positioning System Using Walking Pattern Classification, *Proc. of 22nd IEEE Mediterranean Conference on Control and Automation*, Palermo, Italy, 2014.

[2] De Cillis, F., De Simio, F., Faramondi, L., Inderst, F., Pascucci, F., Setola, R., Improving Situational Awareness for First Responders, *Proc. of CRITIS*, Limassol, Cyprus, 2014.

[3] Faramondi, L., Inderst, F., Pascucci, F., Setola, R., and Delprato, U., An enhanced indoor positioning system for first responders, in *Proc. of the 4th Int. Conf. on Indoor Positioning and Indoor Navigation*, Montbéliard–Belfor, France, 2013.

[4] Faramondi, L., Inderst, F., Panzieri, S., Pascucci, F., Hybrid map building for personal indoor navigation systems, *Proc. of IEEE/ASME Int. Conf. on Advanced Intelligent Mechatronics*, 2014.

[5] Wienberg, H., Using the ADXL202 in Pedometer and Personal Navigation Applications, *Analog Devices AN-602 application note*, 2002.