МЕЛКОМАСШТАБНОЕ ПОЗИЦИОНИРОВАНИЕ С ИСПОЛЬЗОВАНИЕМ ЦИФРОВЫХ КОМПАСОВ

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Представлен метод точной мелкосерийной локализации с использованием подхода «обратного компаса». Стационарные магнитометры отслеживают местоположение мобильного постоянного магнита. В то время как современные системы локализации в помещении стремятся к достижению пометровой локализации в помещениях и зданиях, мы подчеркиваем необходимость создания точных систем локализации сантиметрового уровня, даже с ограниченным охватом. Экспериментальная оценка прототипа показала 3,4 см медианную точность 3D-локализации в тестовом пространстве 20 × 20 × 10 см.

Ключевые слова: внутреннее позиционирование, взаимодействие человек-компьютер, цифровые магнитометры.

SMALL-SCALE POSITIONING USING DIGITAL COMPASSES

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A method for precise small-scale localization using an “inverse compass” approach is presented. Stationary magnetometers track the location of a mobile permanent magnet. While current indoor localization systems strive to achieve sub-meter localization performance in rooms and buildings, we highlight the need for a centimeter-level precise localization systems, even with a limited coverage. Experimental evaluation of a prototype system demonstrated 3,4 cm median 3D localization accuracy within the 20×20×10 cm test space.

Keywords: indoor positioning; human-computer interaction; digital magnetometers.

INTRODUCTION

The indoor positioning researches are usually focused on providing reliable and accurate localization performance at a scale of a building or an apartment [1]. Typical radiobased systems provide an accuracy of few meters [1], which is sufficient for room-level indoor navigation and general context awareness. However, a number of areas would benefit from more precise localization techniques, even if at smaller scales. Cooking, grooming and gesture-based human-computer interaction are some examples of activities which are performed in bounded areas which require precise centimeter-level motion tracking.

This paper explores precise small-scale positioning using magnetic fields. We employ stationary digital magnetometers in order to estimate the location of a permanent magnet (for instance, a magnetic ring on a finger). In this setup, the mobile part does not require batteries, while stationary magnetometer sensors are cheap, power-efficient and fundamentally unable to invade user's privacy. Experimental evaluation of a simple geometric localization algorithm demonstrated few-centimeters accuracy with minimal computation.

RELATED WORK

Small-scale tracking of motion and human activity have previously been addressed by computer vision, wearable sensors and RFID technology. Currently gesture-based human-computer interaction can be monitored using video-based approaches [2, 3] which are computationally expensive, sensitive to illumination conditions and may raise privacy concerns [4]. Wearable sensors can provide information about limb motion (acceleration, direction), but not an absolute position in space. Finally, RFID readers can detect RFID tags nearby, but such localization is often too coarse for the mentioned use cases.

Computer vision is widely used for object tracking and recognition of human activity from hand gestures to general daily tasks [5]. Due to the algorithmic complexity of the task, the objects of interest are often tagged with color markers (such as colored glove [6]). The advance of consumer-grade depth-sensing cameras (such as Microsoft Kinect) enriched the researchers with a new dimension for sensing. Such 3D cameras have been successfully applied to hand tracking [7], recognition of sign language [6] and cooking activities [3].

Vision-based methods can achieve sub-millimeter precision of contract-free tracking (for example, Leap Motion controller [2]). However, there are a number of limitations restricting their use in ambient sensing. The cameras need to have a clear view of the tracked area, preferably at a fixed view point with static lighting conditions [5]. Video processing algorithms are resource-intensive and thus are not suitable for battery-powered sensor nodes. Finally, video cameras can be a threat to personal privacy (or at least perceived so), which limits their adoption in smart homes [4].

Alternative approaches to small-scale activity monitoring employ wearable sensors and RFID tracking. Typically, RFID tags are attached to the objects of interest, whereas the user wears a glove [8] or a bracelet [9, 10] with inertial sensors and an RFID reader. Such a setup makes it possible to recognize when the user holds and manipulates an object. Unfortunately, current wearables have rather limited battery life and require daily recharging, which is not feasible in assisted daily living scenarios.

Another research direction focuses purely on RFID-based localization [11]. In contrast to the video-based methods, RFID readers do not require line of sight and can identify multiple tags simultaneously. However, as RFID localization works by detecting the presence of tags within the reader's antenna field, the accuracy of such systems is limited by the spatial density of reader antennas and the considerable cost of the readers.

Magnetic tracking has been introduced as a method for interaction with mobile devices [12, 13]. Recently, magnetic tracking has been proposed as a method for larger-scale indoor activity monitoring with multiple magnetometer sensors [14]. This paper extends [14], moving from coarse-grained detection of magnetic fluctuations around sparsely distributed sensors towards fine-grained localization using collocated magnetometers.

SMALL-SCALE MAGNETIC POSITIONING

The proposed approach elaborates upon the "inverted compass" concept presented in [14]. The concept enabled coarse-grained localization and activity detection using a wearable permanent magnet and several magnetometer sensors embedded into the environment. When the user passed near one of the sensors, the latter could detect magnetic fluctuations and thus the user's presence. In the present paper, we go further and explore fine-grained localization using actual field strength values reported by the magnetometers.

Physical background

In order to simplify calculations, we made a number of rather strong assumptions. Firstly, the magnet is considered to be negligibly small in comparison to the compass-to-magnet distances. Secondly, physical dimensions of the compasses are also considered to be negligible and their technical characteristics to be the same. Finally, we kept the magnet at a distance from the sensors in order to avoid strong saturating fields and possible permanent magnetization of the devices [15, p. 11].

The intensity of magnetic field H produced by a magnet at a distance d is inversely proportional to d^3 [15, p. 5]: $H \propto M_1 / 4\Pi\mu_0 d^3$, where M_1 is the magnetic moment of the magnet and μ_0 is the permeability of vacuum. Assuming that the environment, sensors and the magnet do not change, we can combine all the constants into one coefficient β, and express the distance magnetic flux density readings of the compass sensor:

$$d = \beta B^{-3} \tag{1}$$

Since all the compasses are assumed to be the same, the value of β depends only on the specific setup and can be calculated using the calibration procedure described below.

The sensors are located in a rectangular area with known dimensions (Figure 1). After trivial geometric transformations, one can express the coordinates of the magnet (x,y,z) using its distance to each compass (d_i).

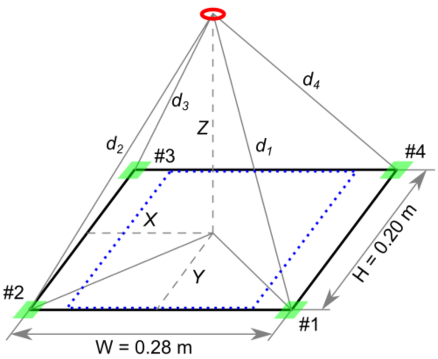

Fig. 1. Sensor setup layout. Green squares are the magnetometers; red ring represents the magnet

Calibration

The calibration is performed in two steps. First of all, we take into account background magnetic fields, such as the planet's own field and local magnetic anomalies. In this phase, the magnet is taken away and all sensor readings are recorded as the initial bias value. This value is then removed from all the future raw readings.

Then, the system evaluates the value of β for the given setup. The magnet is placed in the center of the monitored area, in-plane with the sensors. Since both ground-truth location of the magnet and sensor readings are known, the calibration constant β can be easily inferred from the Equation 1. In practice, these values slightly differ between sensors, so the common constant is calculated as the average of the candidate values.

EXPERIMENTAL EVALUATION

The proposed approach has been evaluated with a custom-built hardware prototype made from off-the-shelf electronic components (Figure 2). Initially we used three digital magnetometers HMC5883L [16], since theoretically three sensors are sufficient for 3D localization. However, early experiments demonstrated accuracy degradation in the area without a sensor, so we added the fourth magnetometer. As the sensors are controlled via the I^2C bus and have the same address, they were connected to an I^2C multiplexer TCA9548A [17], which was queried by a Raspberry Pi [18] board.

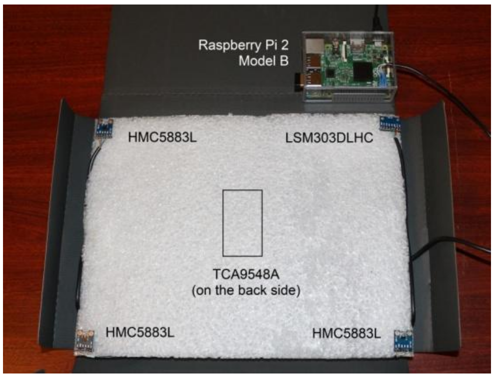

Fig. 2. Hardware prototype (open)

Sensor breakout boards were pinned into a sheet of foamy plastic and encased into a 1-mm thick cardboard box (see Figure 2). The layout and the dimensions of the prototype are shown in Figure 1. The foam ensured that the sensors are as close to the surface of the box as possible. The 12-bit analog-to-digital converters of the magnetometer sensors were configured for the 4.0 Ga range with sensitivity of 440 least significant bits per Gauss.

Experimental setup

The measurements were performed with a 22-mm magnetic ring; due to the generic origins of the sample, its other technical characteristics were not available. The ring was fixed on a plastic whiteboard marker, which enabled us to specify ground-truth 3D location of the magnet with approximately 5 mm precision.

Before data acquisition, the sensors were calibrated to remove the influence of background magnetic fields. To avoid sensor saturation, measurements was confined to the central 200 × 200 mm square of the prototype (blue dotted area in Figure 1). Vertical coordinates ranged from 0 to 100 mm. All measurements were performed along a 20-mm grid for each coordinate, resulting in 10 × 10 × 6 = 600 locations. For each location we recorded raw readings of all the sensors. Calibration data for the β coefficient was recorded separately in the beginning of the session and processed offline during the data analysis.

Results

Figure 3 demonstrates the localization performance of the 4-sensor setup. Black dotted line is a baseline reference, representing an algorithm returning random coordinates uniformly distributed within the measurements area. Median error distance in 3D space was 34 mm (50 mm at 95 % level).

Interestingly, the main source of localization error is the *z* coordinate. If the *z* component is excluded from the error distance calculation, the median error of the resulting 2D localization system improves from 34 mm to only 7 mm (17 mm at 95 % level), as shown in Figure 3. This could be due to imprecise calibration which results in inaccurate estimation of the distances.

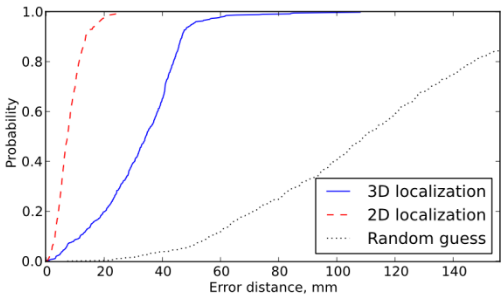

Fig. 3. Localization performance of the prototype

One of the possible ways to reduce the localization error, especially along the *z* axis, is to add an off-plane sensor. While this might not be feasible in some scenarios (for instance, cooking with sensors beneath the table surface), the increased accuracy could be beneficial for interaction and gesture recognition in controlled environments. However, evaluation of such a setup is beyond the scope of this paper.

DISCUSSION AND FUTURE WORK

As any other approach, small-scale magnetic positioning has its weaknesses. On one hand, the limited resolution of the sensors restricts the maximum operating range of the system to about 1~m when used with a strong rare-earth magnet [14]. In addition, the magnetometers must be stationary and are nevertheless susceptible to fluctuations of the background magnetic fields and high-power electric appliances operating nearby. Also, in the current implementation, the system can track only one magnet/object and is fundamentally unable to recognize its identity.

On the other hand, permanent magnets do not require batteries and can be integrated into the objects of interest or safely [19] worn as a ring or a bracelet. Stationary magnetometers are small, do not require line of sight and can be easily hidden within the environment. The amount of data and the processing algorithm are lightweight and can easily be implemented on an embedded platform. In contrast to video-based methods, magnetic localization is fundamentally unable to capture images and thus intrude user's privacy. Finally, our method could provide a quick and simple solution for non-standard scenarios, such as animal behavior tracking. While the coverage area of the presented system is rather limited, it can be increased by installation of additional sensors. The system naturally integrates with the larger-scale magnetic localization system presented in [14]. We are currently evaluating the scalability and performance limits of the system and exploring possible applications in ambient interaction and augmented reality.

ACKNOWLEDGMENTS

This work was partially supported by the National Research Fund of Luxembourg (INDOORS project, grant number C14/IS/8311593).

REFERENCES

1. Survey of wireless indoor positioning techniques and systems / H. Liu [et al.] // IEEE Trans. on Syst., Man, and Cyber., Part C: Applications and Reviews. 2007. Vol. 37, № 6. P. 1067–1080.
2. Analysis of the accuracy and robustness of the Leap Motion controller / F. Weichert [et al.] // Sensors. 2013. Vol. 13, № 5. P. 6380–6393.
3. Lei J., Ren X., Fox D. Fine-grained kitchen activity recognition using RGB-D // Proceedings of UbiComp–2012. ACM, 2012. P. 208–211.
4. Cook D. J., Krishnan N. Mining the home environment // J. of intelligent information systems. 2014. Vol. 43, № 3. P. 503–519.
5. Poppe R. A survey on vision-based human action recognition // Image and vision computing. 2010. Vol. 28, № 6. P. 976–990.
6. American sign language recognition with the Kinect / Z. Zafrulla [et al.] // Proceedings of ICMI-2011. ACM. 2011. P. 279–286.
7. Van den Bergh M., Van Gool L. Combining RGB and ToF cameras for real-time 3D hand gesture interaction // Proceedings of WACV–2011. IEEE. 2011. P. 66–72.

8. Ju Z., Liu H. Human hand motion analysis with multisensory information // IEEE / ASME Transactions on Mechatronics. 2014. Vol. 19, № 2. P. 456–466.

9. Recognizing daily activities with RFID-based sensors / M. Buettner [et al.] // Proceedings of UbiComp–2009. ACM. 2009. P. 51–60.

10. Wearable activity tracking in car manufacturing / T. Stiefmeier [et al.] // IEEE Pervasive Computing. 2008. № 2, P. 42–50.

11. Ni L. M., Zhang D., Souryal M. R. RFID-based localization and tracking technologies // Wireless Communications, IEEE. 2011. Vol. 18, № 2. P. 45–51.

12. Magnetic interaction with devices: A pilot study on mobile gaming / S. Afshari [et al.] // Proceedings of NordiCHI–2014. ACM. 2014. P. 891–894.

13. Ketabdar H., Yuksel K. A., Roshandel M. MagiTact: Interaction with mobile devices based on compass (magnetic) sensor // Proceedings of IUI–2010. ACM. 2010. P. 413–414.

14. Popleteev A. Activity tracking and indoor positioning with a wearable magnet // Adjunct proceedings of UbiComp / ISWC–2015, Osaka, Japan, Sep. 7–11 2015. P. 253–256.

15. Chikazumi S. Physics of Ferromagnetism. 2nd ed. Oxford University Press. 2009. № 94.

16. Datasheet: Three-axis digital compass IC HMC5883L, Honeywell International Inc., 2010.

17. Datasheet: TCA9548A Low-voltage 8-channel I2C switch with reset, Texas Instruments, 2015.

18. Raspberry Pi Foundation. Raspberry Pi 2 model B. 2015.

19. Schenck J. F. Safety of strong, static magnetic fields // J. of magnetic resonance imaging. 2000. Vol. 12, № 1. P. 2–19.