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Exploiting wearable devices for the calibration of inertial navigation systems

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***Abstract*—Wearable devices have many applications, pedestrian navigation among them. In this case, the inertial measurement unit (IMU) is embedded in the wearable device. Moreover, inertial navigation systems (INSs) based on non-foot-mounted IMUs use the step-length-and-heading estimation approach. The latter requires the calibration of the empirical model to estimate the step length. In this work, we propose a method to automatically calibrate empirical models for the step length estimation. Two IMUs are used. The first one is located in some part of the user's body, e.g. the thigh, and it serves the purpose of the inertial navigation. The second is embedded in the shoe, and it is used to calibrate the empirical model of the first IMU. We obtain two main results. Firstly, the calibration is only required during the first two minutes. Secondly, the automatic calibration reduces the distance error in both its mean and standard deviation. This work is subject of a patent application.**

I. Introduction

The miniaturization of inertial sensors is one of the factors that triggered their popularity. They are found not only within smartphones but also within wearable devices, e.g. smart watches. In fact, we foresee that these sensors will be integrated within the clothes in the future. This will encourage the development of inertial-sensor-based applications. In this work, we will focus on inertial navigation.

Inertial navigation for pedestrians follows one of two approaches: strapdown or step-length-and-heading estimation. The authors in [1] present a comparison of these two navigation approaches. The strapdown approach is used with foot-mounted IMUs, whereas the step-length-and-heading estimation approach is used with non-foot-mounted IMUs. There are advantages and disadvantages to each of them. However, it is of high interest to use as many IMUs as possible in order to obtain an improved position estimation by means of combining the information provided by each device. In this paper we propose a method to overcome a common disadvantage for all non-foot-mounted IMUs: the need of an initial calibration.

Inertial navigation with non-foot mounted IMUs uses the step-length-and-heading estimation approach to track iteratively the pedestrian's position. This approach estimates the user's step length in two main steps. The first one is the heading estimation, which is done usually with the turn rate measurements. The second one is the step length estimation, which is done with an empirical model. The latter requires calibration, which is time consuming and it is prone to errors if the user is not familiar with the procedure.

This disadvantage, i.e. the need for calibration, is handled in the state of the arts in three main ways. The first one is by setting up the model parameters to predetermined values [2]. The second one is by manual calibration, e.g. by walking a predetermined distance [3]. The third one is by using maps [4]. Nevertheless, this disadvantage can be mitigated thanks to the wearable devices. Since IMUs will be integrated within the clothes and the shoes in the future, inertial data from different parts of the body will be available at no additional cost. Therefore, they can be used to either simplify or automate the calibration process.

In this work, we propose to use an IMU embedded in the shoe to calibrate empirical models for the step length estimation. As a proof of concept, we calibrate a model that is based on an IMU introduced in the pocket. The latter could be, for example, a smartphone.

II. Problem statement

Pedestrian dead reckoning with the step-length-and-heading estimation approach requires an estimation of the user's step length. Provided that the pitch (θ) of the user's thigh can be estimated, i.e. by a thigh-mounted IMU as in Fig. 1, the user's step length (s_k) at the k-th time can be modelled as [5]:

$$s_k = a \cdot \Delta\theta_k + b + e_k, \tag{1}$$

where $\Delta\theta_k$ is the amplitude of the thigh pitch at the k-th time and (a, b) are the parameters of the first-order regression-line model. The term e_k is an unobservable random variable that represents the error in the model [6].

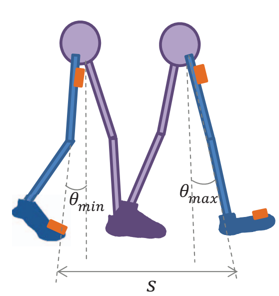

Fig. 1: Maximum and minimum thigh aperture (pitch) during the walk.

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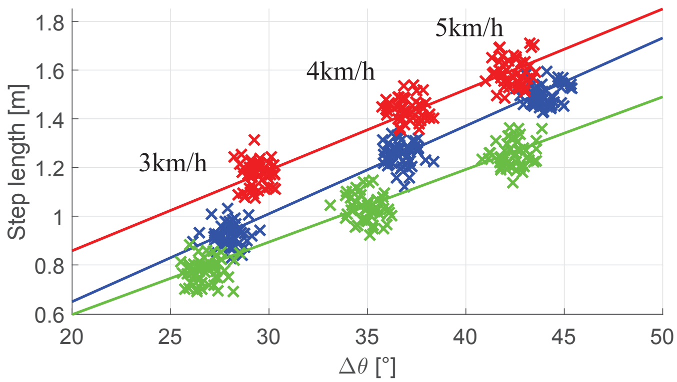

Fig. 2: Empirical model of the step length based on the opening angle of the leg while walking. Each line represents a different pedestrian.

The model is presented in Fig. 2, where the data of three users is represented in a different color. Each step is represented by a cross mark [3]. The main drawback of the model is that it requires the use of universal parameters. The latter are estimated to fit the regression lines of a set of users. That is, the parameters do not model optimally the regression line of a single user.

Fig. 2 shows that the model slope, a, is similar between individuals as compared to the differences in the offset, b, [5]. Based on this, the author in [3] proposes to calibrate the model (1) in two steps. Firstly, the slope a has to be fixed to the universal value. Secondly, the offset b has to be estimated by walking a known distance, [3]. Although effective, this approach requires to know the distance of a specific path. It also requires that the user, prior to use the INS, performs a walk dedicated solely to the calibration.

Let us assume that there is inertial data from the user's foot available, for example, because an IMU is integrated in the user's shoe. In that case, information about the user's step length can be obtained by means of the foot IMU [1]. This information can be used then to calibrate the model (1). Moreover, since the calibration is required only at the beginning of the walk, the foot IMU can be powered off once the calibration is completed.

The problem statement in this work is, thus, how to estimate the offset b in model (1) for a pedestrian that is wearing simultaneously two IMUs.

III. Automatic Calibration

The automatic calibration estimates the offset b for each individual by profiting from the knowledge of the step length through the IMU embedded in the shoe [1]. The following sections present the two proposed approaches for the automatic calibration of the step length model in (1).

Option 1

In this case, the offset b is estimated during the first n steps as follows:

$$b = \frac{1}{n} \cdot \sum_{k=1}^{n} (s'_k - a \cdot \Delta\theta_k), \tag{2}$$

where the subindex k indicates the k-th step, s'_k is the step length known thanks to the foot-mounted IMU and $\Delta\theta_k$ denotes the amplitude of the thigh pitch.

Equation (2) addresses the challenge identified in the previous section. That is, equation (2) allows for the personalized and automatic estimation of the offset b. In addition, the calibration time requires only n steps. Under the assumption that a user walks one step per second, this method would require n seconds to automatically calibrate the model in (1).

The offset b estimated by this method depends on the number of steps n. Therefore, it is not possible to assure that the estimated b is the optimum for the user. For instance, Fig. 2 shows that for a given walking speed, the pairs (step length, $\Delta\theta$) are distributed in a cloud around the optimum point. If the slope of the regression line is set to a fixed value, then there should be an offset that fits the best the cloud of points. To address this issue, the next option is proposed.

Option 2

The second proposed calibration method is based on the least squares approach. Let s'_k be the step length at the k-th time which is known thanks to the foot-mounted IMU. The mean squared error in the step length estimation, $\xi(b)$, is given by:

$$\xi(b) = \sum_{k=1}^{n} (s'_k - a \cdot \Delta\theta_k - b)^2, \tag{3}$$

where n is the total number of steps. The energy of the error can be plotted against the plausible values of the offset, b, for any test walk, e.g. Fig. 3. Mathematically speaking, the offset b can take any real value. However, physically speaking, its value is constrained to a certain range. The value of b depends on the value of the slope, a, and the amplitude of the thigh pitch, $\Delta\theta$, while walking. The first one, a, is fixed to the universal value which is in the order of 0.05$m/°$. The second one, $\Delta\theta$, ranges from 15°to 60°depending on the walking speed [3]. Given that, the human step length is between 0.5m and 1.5m, depending on the user's height and walking speed, the values of b are usually constrained to, as maximum, $\pm 1m$. This limitation in the values of b is necessary to understand why, in Fig. 3, the offset b has been represented only in the range $\pm 10m$. Furthermore, this limitation is necessary to assure the feasibility of the next step, i.e. the minimization of (3).

Fig. 3 shows that, in the range where b is suitable for model (1), there is a single value of b that minimizes the energy of the error. This value satisfies that:

$$\frac{\partial \xi(b)}{\partial b} = 0. \tag{4}$$

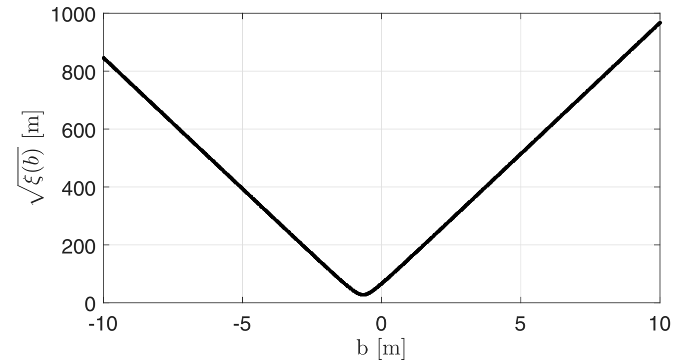

Fig. 3: Root mean squared error in the step length for a walk with a duration of approximately 7.5 minutes.

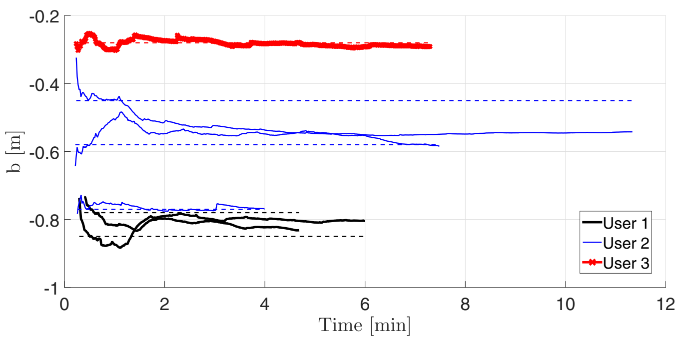

Fig. 4: Recursive estimation, by *Option 2* of the offset b during the test walks (solid lines). Each solid line represents a different walk. For each solid line, a dashed lines is plotted for comparison. The dashed line indicates the offset estimated by *Option 1* with n set to 10 steps.

Therefore, solving the previous equation for the offset b results in:

$$b_k = \frac{1}{n} \sum_{k=1}^{n} \left(s'_k - a \cdot \Delta\theta_k \right), \tag{5}$$

The latter can be seen as a low-pass filtered estimation of the offset b over all the steps. In addition to minimizing the squared error, (5) is simple and it can be implemented recursively:

$$b_k = b_{k-1} \cdot \frac{k-1}{k} + \frac{s'_k - a \cdot \Delta\theta_k}{k}. \tag{6}$$

This recursive equation avoids the need for saving information such as the set of s'_k values.

Fig. 4 presents, in solid lines, the offset b estimated according to (6) for 3 users during 6 walks. It can be seen that the offset estimation converges after 2 minutes approximately. The convergence of the offset indicates that the calibration only requires a limited time at the beginning of the walk. After that time, which we denote as convergence time, no more data from the foot IMU is required. Thus, the foot IMU can be shutdown in order to, for example, save power.

An interesting result in Fig. 4 is that the offset, b, of *User 2* presents two different values. That is because one of the walks was performed on a different day and with the IMU in a different location on the thigh. This behaviour shows an advantage of the proposed algorithm. The automatic calibration will estimate the offset that better fits the model (1), although the pocket IMU is located in a different part of the thigh.

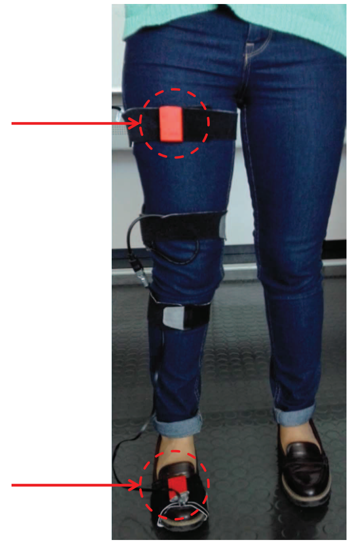

Fig. 5: IMU setup during the experiments. One IMU is placed on the upper thigh. The other IMU is placed on the front part of the foot.

IV. Evaluation

This section presents the results of evaluating the calibration methods proposed above.

A. Evaluation methodology

There are two main points regarding the evaluation methodology: the experiments and the ground truth system. The experiments are done to collect data that will be processed with the INS based on a thigh-mounted IMU. The INS implements each of the calibration methods proposed above. The ground truth system provides an objective way to evaluate the navigation systems regarding their position estimation.

As for the experiments, inertial measurements were recorded from two IMUs simultaneously. One IMU was placed on the foot and the other one was placed on the thigh, see Fig. 5. Further details about the experiments' methodology are given in [1].

As for the ground truth system, it consists of a set of ground truth points (GTPs). These GTPs are points with known location. Their location is measured with a laser distance measurer and a tachymeter system, further details are given in [1]. The GTPs are visited during the experiments. The collected data is processed off-line with the pocket INS implementing each of the two proposed calibration methods. The position of the GTPs estimated by the pocket INS is compared to the true

TABLE I: Mean (μ) and standard deviation (σ), written as $\mu \pm \sigma$, of the distance error of the two calibration methods presented. The errors of the INS implemented with the generic parameters are also given.

	Universal parameters	Option 1	Option 2
$e_{\Delta d}[m]$	-6.7 ± 6.8	-0.2 ± 2.4	0.3 ± 1.8

position regarding the distance between consecutive GTPs. For that purpose, the distance error ($e_{\Delta d}$) is defined as follows:

$$e_{\Delta d} = d_{ij}^{GTP} - d_{ij}^{INS}, \tag{7}$$

where d_{ij} refers to the Euclidean distance between the i-th and j-th GTP. The superscripts GTP and INS refer to the source of the parameter, i.e. the ground truth points or the INS respectively. The error metric (7) is used because the trajectory between GTPs is, approximately, a straight line.

A total of 184 GTPs were visited during 17 walks. T distance error is computed for each GTP. The mean (and standard deviation (σ) of these errors are presented a discussed in the next section.

B. Results and discussion

The evaluation results are presented in Table I. *Universal parameteres* denotes the INS which implements the universal values of a and b. *Option 1* and *Option 2* denote the INS that implements the calibration methods proposed in Section III.

The results in Table I show that, with respect to the *Universal parameters*, the proposed methods reduce both the mean and standard deviation of the distance error. In fact, the mean distance error is reduced by a factor of 33.5 in the case of *Option 1* and a factor of 22.3 in the case of *Option 2*. Furthermore, the standard deviation is reduced by a factor of 2.8 in *Option 1* and a factor of 3.8 in *Option 2*. In addition, the automatic calibration eases the use of the pocket INS.

In comparing the two methods for automatic calibration, it can be seen that *Option 2* has the lowest standard deviation. However, it is *Option 1* that achieves, in absolute value, the lowest mean error. The reason might be that *Option 2* is designed to minimize the squared error in step length, see (3), instead of to minimize the mean error in step length.

An interesting result is that equations (2) and (5) are, with the exception of the time index k, the same. However, these two equations have a different principle of application. *Option 2* does not limit the number of steps. That is, the value n in (5) considers the overall number of steps detected until the k-th time. In contrast, the value n in (2) refers only to the fi n steps during the walk. After the first n steps are detecte *Option 1* uses the estimated offset b. Therefore, the offse estimated by each calibration method is different dependi on the initial number of steps n that is set for *Option 1* .

Fig. 4 is an example of the differences between the offset estimations of both calibration methods. The number of steps n of *Option 1* is set to 10. The estimations of both methods coincide only for *User 3* and one walk of *User 2*. However, in the rest of the cases, the differences are of several cm. In contrast, Fig. 6 shows more similar estimations of the offset b than Fig. 4. The reason is that n in *Option 1* has been increased to 120 steps. That is, the larger the n of *Option 1*, the more similar the b estimations of each calibration method will be.

Fig. 7 and Fig. 8 present the odometry estimated by the pocket INS for an indoor walk. The odometry with the universal parameters, solid line, has a shorter length that the actual walk. This fact can be seen because the circle markers that correspond to the GTP identifiers 78 and 89 are not on the associated cross mark. In contrast, the odometry with the automatic calibration presents, in both cases, a better length estimation. The latter can be appreciated through the location of the circle markers that correspond to the GTP identifiers 78 and 89, which is approximately the same as the location of the associated cross marks. It is worth noticing that, although

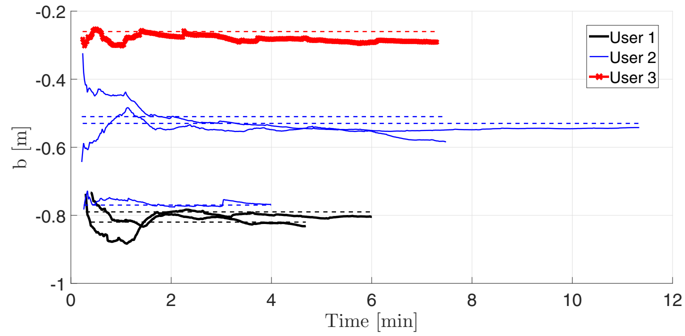

Fig. 6: Recursive estimation, by *Option 2* of the offset b during the test walks (solid lines). Each solid line represents a different walk. For each solid line, a dashed lines is plotted for comparison. The dashed line indicates the offset estimated by *Option 1* with n set to 120 steps.

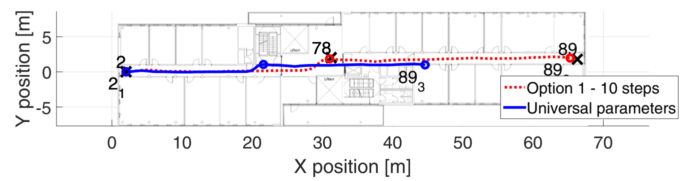

Fig. 7: Odometry of an indoor walk for the pocket INS. The cross marks indicate the GTPs. The circle marks indicate the position estimated by the odometry for the cross marks.

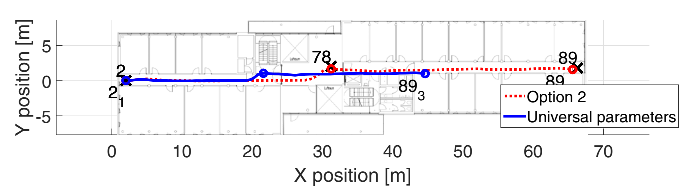

Fig. 8: Odometry of an indoor walk for the pocket INS. The cross marks indicate the GTPs. The circle marks indicate the position estimated by the odometry for the cross marks.

Fig. 7 and Fig. 8 present similar odometries in the case of the automatic calibration, the error statistics of each calibration method are different, see Table I.

In fact, each alternative has a certain advantage over the other. On the one hand, *Option 1* provides a known calibration time, which is determined by the number of initial steps n. However, the value set for n might not be sufficient to achieve the optimum value of the offset b. On the other hand, *Option 2* provides an optimum estimate of the offset b at the cost of using a larger number of steps than *Option 1*. Nevertheless, Fig. 4 and Fig. 6 show that the convergence time is approximately 2 minutes. The common factor to both options is the number of steps n. A value n large enough would make both options to converge to the same solution.

V. Conclusion

This work presents a method to automatically calibrate an inertial navigation system that is based on the step-length-and-heading estimation approach. The proposed method uses the knowledge of the user's step length which is obtained through a foot-mounted IMU. The step length obtained from the foot-mounted IMU is used in two different approaches to automatically calibrate the model for step length estimation.

The results show that the automatic calibration of the pocket INS is feasible. In fact, the model calibrated automatically provides more accurate results than the model with universal parameters. According to the results, the calibration is required, in the worst case, during only the initial 2 minutes. In the case that the calibration becomes obsolete, e.g. because the pocket IMU has moved, a new automatic calibration can be triggered. That is, the automatic calibration favours the seamless operation of the INS based on the step-length-and-heading estimation approach.

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