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Novel Noniterative Orientation Estimation for Wearable Motion Sensor Units Acquiring Accelerometer, Gyroscope, and Magnetometer Measurements

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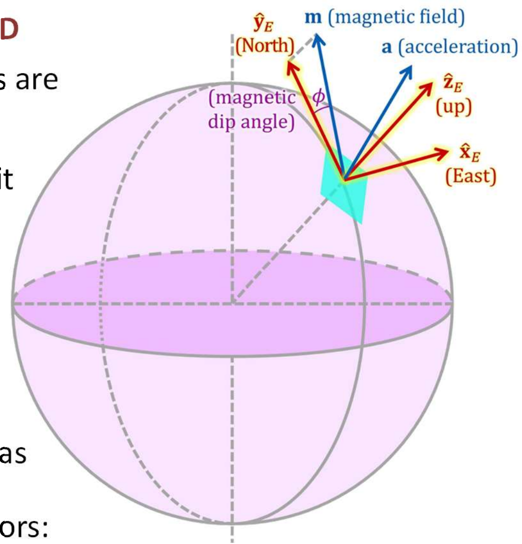
We propose a novel noniterative orientation estimation method (OEM) for wearable motion sensor units based on the physical and geometric properties of the sensors and the estimated value of the magnetic dip angle. We comparatively evaluate the proposed method in recognition of daily and sports activities that requires accurately estimated wearable sensor unit orientations. The proposed method achieves a higher accuracy and better computational efficiency than the state-of-the-art methods [1].

INTRODUCTION AND BACKGROUND



The following measurement vectors are acquired from the accelerometer, gyroscope, magnetometer of an inertial/magnetic measurement unit (IMMU), respectively: $\mathbf{a}$, $\boldsymbol{\omega}$, $\mathbf{m}$.

Measurements are normalized by their norms as $\hat{\mathbf{a}} \triangleq \mathbf{a}/\|\mathbf{a}\|$.

The orientation quaternion $\mathbf{q}[n]$ relative to the earth frame E (with axes $\hat{\mathbf{x}}_E, \hat{\mathbf{y}}_E, \hat{\mathbf{z}}_E$) at time sample n can be estimated as

- **static estimate ($\mathbf{q}_s[n]$)** based on the two reference vectors:
  - the gravity detected by the accelerometer
    - summed by the acceleration caused by the motion
  - the earth's magnetic field measured by the magnetometer
    - superposed with magnetic distortion
  - ➥ *accurate in the long term*
- **dynamic estimate ($\mathbf{q}_d[n]$)** based on the gyroscope, obtained by integration
  - suffers from bias error
  - ➥ *accurate in the short term*

These estimates need to be fused to obtain a combined estimate.

RELATED WORK

- Deterministic approaches: The static estimate is obtained using simple methods such as TRIaxial Attitude Determination (TRIAD) or optimization techniques such as Gradient-Descent (GD), Gauss-Newton (GN), and Levenberg-Marquardt (LM) optimization. Most of these methods fuse the static estimate and the dynamic estimate (calculated using simple integration) by weighted averaging.
- Stochastic approaches directly calculate the combined orientation using techniques such as different types of Kalman filters (KF) and particle filters (PF) at high computational cost.

PROPOSED METHOD

We estimate the **dynamic orientation** based on the previously obtained combined estimate $\mathbf{q}[n]$ as

$$\mathbf{q}_d[n] = \mathbf{q}[n-1] + \Delta t \left(\frac{1}{2} \mathbf{q}[n-1] \otimes \boldsymbol{\omega}'[n] \right)$$

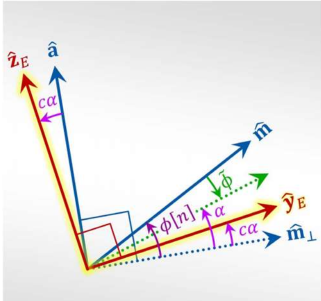
where $\boldsymbol{\omega}'[n] \triangleq (0, \boldsymbol{\omega}[n])^T$, $\otimes$ denotes the quaternion product operator, and Δt is the time step.

PROPOSED METHOD *(continued)*

For the **static orientation**, we estimate the **magnetic dip angle** ϕ by averaging the angle between $\mathbf{m}[n]$ and the horizontal plane (perpendicular to $\mathbf{a}[n]$) over a short time segment of N samples:

$$\boxed{\tilde{\phi} = \frac{1}{N} \sum_{n=1}^{N} \phi[n]} \quad \text{where} \quad \phi[n] = \frac{\pi}{2} - \angle(\mathbf{a}[n], \mathbf{m}[n]).$$

The following objectives are imposed:
O1: align $\hat{\mathbf{z}}_E$ with $\hat{\mathbf{a}}$.
O2: set the angle between $\hat{\mathbf{y}}_E$ and $\hat{\mathbf{m}}$ to the estimated dip angle $\tilde{\phi}$.
O3: select $\hat{\mathbf{y}}_E$ and $\hat{\mathbf{z}}_E$ perpendicular to each other.



Since O1 and O2 cannot be satisfied simultaneously (unless $\tilde{\phi} = 0$), we compromise between them using the parameter $c \in [0, 1]$ as

$$\boxed{\begin{aligned} \hat{\mathbf{z}}_E &= \hat{\mathbf{a}} \cos(c\alpha) - \hat{\mathbf{m}}_\perp \sin(c\alpha) \\ \hat{\mathbf{y}}_E &= \hat{\mathbf{a}} \sin(c\alpha) + \hat{\mathbf{m}}_\perp \cos(c\alpha) \end{aligned}}$$

where $\alpha = \mathrm{sign}(\mathbf{a} \cdot \mathbf{m})\big(\phi[n] - |\tilde{\phi}|\big)$ and $\hat{\mathbf{m}}_\perp = \mathbf{m}_\perp / \|\mathbf{m}_\perp\|$ with $\mathbf{m}_\perp = \mathbf{m} - (\hat{\mathbf{a}} \cdot \mathbf{m})\hat{\mathbf{a}}$.
We select the remaining axis as $\hat{\mathbf{x}}_E = \hat{\mathbf{y}}_E \times \hat{\mathbf{z}}_E$.

We obtain the **overall estimate** through weighted averaging of the dynamic and static estimates:

$$\boxed{\mathbf{q}[n] = \mathcal{K}\mathbf{q}_d[n] + (1 - \mathcal{K})\mathbf{q}_s[n]}$$

where $\mathcal{K} \in [0, 1]$ is the weight parameter of the algorithm.

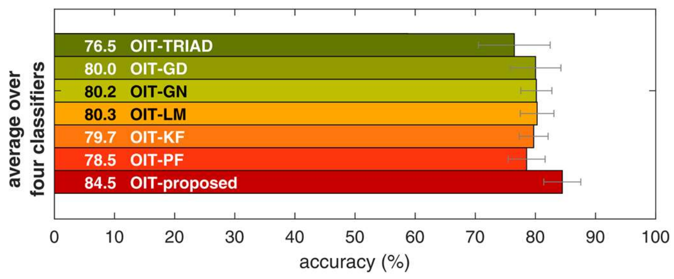
COMPARATIVE EXPERIMENTAL EVALUATION

For a **comparative analysis**, we incorporate the proposed and existing OEMs into an activity recognition scheme based on wearable IMMUs:

- Time-domain data are divided into 5-s segments.
- The orientation of each unit is estimated at each time sample based on the magnetic dip angle estimated for the time segment that the sample belongs to.
- An orientation-invariant transform (OIT) is employed to consider the change in the orientation relative to the earth frame E to allow the units to be worn at any orientation.
- Statistical features are calculated for each segment and normalized.
- Classification is performed using four state-of-the-art classifiers.
- Accuracy is evaluated through leave-one-subject-out cross validation.

We use a publicly available dataset [2] that consists of 19 daily and sports activities performed by eight subjects wearing five IMMUs.

Average activity recognition accuracy over the classifiers and stand-alone run times are presented for the existing and proposed OEMs.



OEM	run time per 5-s time segment (ms)
TRIAD	19.45
GD	13.36
GN	57.66
LM	115.93
KF	91.13
PF	3977.67
proposed	**19.82**

CONCLUSION

The proposed OEM outperforms the existing ones in activity recognition, as well as being computationally more efficient than most of them.

REFERENCES

[1] A. Yurtman and B. Barshan, "Novel non-iterative orientation estimation for wearable motion sensor units acquiring accelerometer, gyroscope, and magnetometer measurements," *IEEE Trans. Instrum. Meas.*, 69(6):3206-3215, June 2020.
[2] K. Altun and B. Barshan, "Daily and sports activities dataset," IEEE Data Port, Feb. 2019.