

Personal navigation with handheld devices Valérie Renaudin

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IPIN 2015 TUTORIAL

Personal Navigation with Handheld Devices

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Banff, Canada, 13 October 2015



Instructor Bio: Valérie Renaudin

Current

 Head of GEOLOC Lab at the French institute of science and technology for transport, development and networks (IFSTTAR)

Graduation

- MSc in Geomatic Eng. from the ESGT, France
- PhD in Computer, Communication and Information Sciences from the EPFL, Switzerland

Research Focus is on

- Methods and systems for personal mobility in multimodal transport
- Pedestrian navigation using signals from Global Satellites Navigation Systems, inertial and radio telecommunication technologies in indoor spaces

Past Positions





IFSTTAR

FRENCH INSTITUTE OF SCIENCE AND TECHNOLOGY FOR TRANSPORT, DEVELOPMENT AND NETWORKS

20

0101 (010)

23



A Paradigm Shift!







Why navigating with handheld devices?

PAST/PRESENT

 Strapdown navigator in motorized bodies → physics of solid



• Principally outdoors



 General navigation functionalities





FUTURE

- Connected human → not well known human kinematic
- Indoors → 70% of mobile phone calls and 80% of data telecom in indoor spaces [Strategy Analytics 2012]
- The smartphone is a toolkit for everything including navigation
- We want the connected object to understand my particularities: Who am I? Physiological parameters?



Targeted performances

- Continuous, reliable and accurate
- In figures
 - 1 m accuracy
 - 95% percentile of the error distribution law
 - 99% coverage
- Applications from recreational use up to safety critical services

Shopping Mall in Nantes : Passage Pommeraye



Beyond Navigation Expectations

- Adaptive to all dynamics
 - Different motion modes
 - Comfortable walking
 - walking disabilities
 - Active transport
 - walk, run, bike
 - Motorized transport
 - private car
 - public transit
- Providing personal (positive) feedback
 - on physiological performance: a training tool
 - on general health: a medical diagnostic tool

The development of consumer navigation systems is more and more pedestrian's centered

Overview and motivation



GEOGRAPHICAL FRAMES

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des Forêts

Many different coordinate frames

- Inertial Navigation involves several coordinate frames
 - Inertial Frame (Inertial Signals)
 - Earth Centered Earth Fixed Frame (GNSS)
 - Local Frame (Map)
 - Body Frame (IMU)
 - Pedestrian Frame (Handheld Sensor)
- Preliminary comments
 - The definition of these frames may differ depending on the application and the context
 - These choices impact the mechanization equations of inertial navigation



Inertial Frame (i-frame)

- The inertial frame is close to a Galilean frame
 - non-rotating & non accelerating frame
- The approximation comes from the fact that the earth is accelerating while it orbits the sun
- Accelerometer and gyroscope
 measurements are given in this frame



http://hronrad.wordpress.com/

| Parameter | Description | |
|-----------|--------------------------------------|--|
| Origin | Earth's Center of Mass | |
| Z axis | axis Parallel to the earth spin axis | |
| X axis | Pointing toward mean vernal equinox | |
| Y axis | Form a right handed orthogonal frame | |



Earth Centred Earth Fixed Frame (eframe)

- Principally used for satellite signals based navigation (GPS, GLONASS, Beidou, Galileo) because orbital data are computed in this frame
- Also called terrestrial equatorial frame
- Satellite signals and inertial navigation are often combined in this frame



| Parameter | Description |
|-----------|---|
| origin | Earth's Centre of Mass |
| Z axis | Parallel to earth spin axis |
| X axis | Pointing towards mean meridian of Greenwich |
| Y axis | Completing right-handed orthogonal frame |



Local Frame (I-frame)

- Its choice and axis convention depend on the application
- On the illustration: North, East, Down (N,E,D)
- Often linked to the geographic information system used to display the navigation solution



| Parameter | Description | |
|--|--|--|
| origin | Arbitrary: point on the earth surface | |
| Z axis Orthogonal to the reference ellipsoid | | |
| Y axis | Directed to the geodetic north | |
| X axis | Completing right-handed orthogonal frame | |

Transformation between e-frame and i-frame

• The Xn, Yn, Zn axes of the I-frame are expressed in the e-frame with



Body Frame (b-frame)

- The body frame can be defined in many different ways
- Usually right-handed 3D Cartesian frame related to an object
- In strapdown applications, the body frame is considered as rigidly attached to the vehicle
- This hyp. doesn't always hold for pedestrian navigation applications



| | Parameter | Description |
|--------|-----------|--|
| | origin | Specific point within the object |
| | X axis | Pointing along the forward direction |
| Y axis | | Pointing along the lateral axis of the IMU |
| | Z axis | Completing right-handed orthogonal frame |



Pedestrian Frame

- The pedestrian frame is attached to the "skeleton" of the human body
- Its origin describes the pedestrian position on the map
- Intermediate frame between the body and the local frames
- Usually right-handed 3D Cartesian frame

| Parameter Description | | |
|---|--|--|
| origin | Human Body Center of Mass | |
| X axis Pointing along the forward direction | | |
| Y axis | Pointing along the lateral axis of the IMU | |
| Z axis | Completing right-handed orthogonal frame | |

120 1203 18.0 HISTORY OF NAVIGATION

History of Navigation



Landmarks Navigation

- Stone age practice
- Recognizing landmarks to deduct geographical locations & find routes

Celestial Navigation

- Observing the geometrical configuration of celestial objects for deriving location and guidance data
- Triangulation: angle measurements between the observer's local vertical and the star (sun or moon)

History of Navigation

Radio Navigation

- Use of radio signals to measure the distance
- Accurate time measurement becomes critical
- At speed of light: 1µsec error gives 300m error
- Trilateration positioning is introduced.

Dead Reckoning

- Estimates the current position based on the previous one and distance/speed, angle measurements extracted from embedded seniors
- A recursive process common for aircraft navigation



History of Navigation

Inertial Navigation

- Is a dead reckoning navigation
- The measurements are accelerations and angular rates relative to an inertial navigation frame
- Processing
 - Estimates the Position, Velocity and Attitude changes of a body
 - Its mechanization is based on Newton's 1st and 2nd law of motion
- Definition
 - INS → Inertial Navigation System
 - IMU → Inertial Measurement Unit



Inertial Sensors

Stable platform

→ A triad of acc. is kept physically aligned with respect to the local vertical and north axes

→ Mechanically complicated, bulky

Strapdown sensors configuration

- \rightarrow Introduced in the early 80s
- → The stabilization is achieved mathematically

→ Smaller size, weight and consumption Micro-Electro-Mechanical Systems: MEMS

 \rightarrow Latest introduced inertial sensors

→ Small and less expensive

 \rightarrow Mass production

→ Embedded in daily life equipment (smartphone, remote control, ...)

→ Consumer Grade sensors

Inertial Sensors → Solid state optics

Solid State

→Nanotechnol ogy

→ Atomic Physics

Operate without reference to an external signal \rightarrow Autonomous with respect to its environment

Gyroscope

- Gyroscopes are angular rate sensors
- Measure the rotation rates of the body frame relative to the inertial frame
- Parameterized in the body frame, it is ω_{ib}^{b}



© Science Museum / Science & Society Picture Library



Gyro. Main Operation Principles

- Spinning Mass
 - Uses the principle of conservation of angular momentum
 - Directions in inertial space are defined by bodies/particles rotating with constant momentum
 - One example is the rotor gyro designed for stable platform
- Optical Gyros
 - Uses Sagnac effect
 - Based on relativistic principle that speed of light is conserved in rotating body
 - Widely used in automotive applications
- Vibratory or Resonator Gyro
 - Uses Coriolis principle
 - An oscillating inertial body will preserve the plane of vibration even under rotation
 - Angular rates are derived from rotating accelerometers to which a high frequency vibration is applied
 - Primary choice for MEMS



Accelerometer

- They are specific force sensors
 - mesure the acceleration plus the gravity:

$$f^{i} = \ddot{x}^{i} - g^{i}$$

- free fall: $\ddot{x}^{i} = -g^{i}$
- the gravitational acceleration needs to be removed from the accelerometer data prior to using it for inertial navigation



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Acc. Main Operation Principles



- Force-rebalanced accelerometer
 - These servo acc. restrain a proof of mass and measure the electrical current needed to supply the restoring force, which is proportional to the acceleration
 - "standard" translational or pendulous design still used
- Vibratory accelerometer (MEMS)
 - Measure the acc. as a frequency difference in a pendulous system
 - Vibrating string acc., quartz resonator or integrated silicon acc.
 - Not as accurate as the force-balanced acc.
- Electrostatic levitated accelerometer (MEMS)
 - Position change of a suspended small element by electrostatic is sensed by a capacitance in a closed-loop servo system
 - High performance acc.



IMU Errors

- All sensors are affected by errors:
 - deterministic & stochastic
- Sensor assembly error linked to orthogonal tri-axis arrangement
 - Sensor axis misalignment
 - Non-orthogonality
 - Nominal scale factor
- For the others, their behavior is described with statistical terms (stochastic processes)
 - in run bias
 - scale factor



- Inertial sensors performances vary a lot depending on the technology and the application
- The quality of inertial sensors depend on
 - the accuracy
 - the dynamic range
 - the sensitivity



Gyroscope Error Model

- A sample single axis gyroscope signal modeling is $\omega(t) = b_{\omega} + S_{\omega}\omega(t) + C_{\omega}(t) + W_{\omega}(t)$
 - b_{ω} is the turn on to turn on bias term
 - $-S_{\omega}$ is the scale factor error term
 - $-C_{\omega}(t)$ is the correlated noise term
 - $W_{\omega}(t)$ is the white noise
- The correlated noise is for example described by a Gauss-Markov process:

$$\dot{C}_{\omega}(t) = \frac{-1}{\tau_{C_{\omega}}} C_{\omega}(t) + W_{C_{\omega}}(t)$$

$$\tau_{C_{\omega}} \text{ is the correlation time}$$

$$W_{C_{\omega}}(t) \text{ is the white noise}$$

Accelerometer Error Model

• A simple single axis accelerometer signal modeling is

$$f(t) = b_f + S_f f(t) + C_f(t) + W_f(t)$$

- f(t) is the specific-force measurement
- $-b_f$ is the turn on to turn on bias term
- $-S_f$ is the scale factor error term
- $-C_f(t)$ is the correlated noise term
- $-W_f(t)$ is the white noise
- Allan variance analysis is often conducted to estimate the parameters of the noise stochastic processes (described in textbooks)



Inertial Sensors Performances

| Sensor | Error | Tactical Grade | Consumer Grade |
|--------------|----------------|----------------------------------|-------------------------------------|
| Gyro | Bias Stability | 0.01 °/hr | 15-100 °/hr |
| Gyro | Noise | 0.2-0.5 °/hr/vHz | N/A |
| Acc | Bias Stability | 0.1 mg | 1-10 mg |
| ///// | Noise | 0.2-0.4 mg/√Hz | N/A |
| | | | |
| Applications | | Tactical Missile, Automotive, | Consumer, Pedestrian Navigation, |





Inertial Navigation Algorithm



INS Equations: Position and Velocity

- Evolution of the velocity (\dot{x}) of the mobile in time
 - $\ \forall u \in [t, \Delta t]$

$$- \dot{\mathbf{x}}_{t+\Delta t}^{n} = \int_{t}^{t+\Delta t} \ddot{\mathbf{x}}^{n} \, du = \dot{\mathbf{x}}_{t}^{n} + \ddot{\mathbf{x}}^{n} \Delta t$$

- Evolution of the position (\mathbf{x}) of the mobile in time

$$- \ \forall u \in [t, \Delta t]$$

$$-\mathbf{x}_{t+\Delta t}^{n} = \int_{t}^{t+\Delta t} \dot{\mathbf{x}}^{n} \, du = \mathbf{x}_{t}^{n} + \dot{\mathbf{x}}_{t}^{n} \Delta t + \frac{1}{2} \ddot{\mathbf{x}}^{n} \Delta t^{2}$$

- With only an accelerometer bias error modeling
 - $\ddot{\mathbf{x}} = \mathbf{f} \mathbf{g} \mathbf{b}_f + \mathbf{w}_f$
 - g is known in local map frame and f measured in the body frame \rightarrow orientation ?



INS Equations: Orientation


INS Equations: Quaternion

- Quaternion modeling of the rotation θ around the vector \mathbf{u} $\mathbf{q}_{a}^{b} = \left(\cos(\frac{\theta}{2}), \sin(\frac{\theta}{2})\mathbf{u}\right)$
- Multiplication in vector form $(0, \mathbf{x}^b) = \left(\cos(\frac{\theta}{2}), \sin(\frac{\theta}{2}) \mathbf{u} \right) \circ (0, \mathbf{x}^a) \\ \circ \left(\cos\left(\frac{\theta}{2}\right), -\sin\left(\frac{\theta}{2}\right) \mathbf{u} \right) \\ (0, \mathbf{x}^b) = \mathbf{q}_a^b \otimes (0, \mathbf{x}^a) \otimes \overline{\mathbf{q}}_a^b$



• $\overline{\mathbf{q}}$ is the conjugate of \mathbf{q}



INS Equations: Orientation

- Acceleration in the local frame
 - $(0, \ddot{\mathbf{x}}^{n}) = \mathbf{q}_{b}^{n} \circ (0, \ddot{\mathbf{x}}^{b}) \circ \overline{\mathbf{q}}_{b}^{n} (0, \mathbf{g}^{n})$
- Evolution of the attitude angles quaternion

$$- \mathbf{q}_{b}^{n}(t + \Delta t) = \mathbf{q}_{b}^{n}(t) \circ \mathbf{q}_{\omega}^{b}(t)$$

• Relation between quaternion and angular rates

$$- \mathbf{q}_{\omega}^{\mathrm{b}}(t) = \begin{pmatrix} \cos(\frac{\|\boldsymbol{\omega}_{\mathrm{nb}}^{\mathrm{b}}\|}{2}\Delta t) \\ \sin(\frac{\|\boldsymbol{\omega}_{\mathrm{nb}}^{\mathrm{b}}\|}{2}\Delta t) \frac{\boldsymbol{\omega}_{\mathrm{nb}}^{\mathrm{b}}\Delta t}{\|\boldsymbol{\omega}_{\mathrm{nb}}^{\mathrm{b}}\Delta t\|} \end{pmatrix} + \mathbf{w}_{q_{\omega}}^{\mathrm{b}}$$

With only a gyroscope bias error modeling
 - ω = ω + b_ω + w_ω



Impact of IMU errors

- Assuming a non-rotating earth and a single plane body dynamic
 - a constant acc. bias error impacts the position (x) at time square rate: Δt^2
 - a constant gyro. bias error will impact the position (x) at time cubic rate: Δt^3
- A correlated problem: azimuth errors are propagated in the horizontal velocity via the specific force
- Solutions consists in
 - adopting aided navigation solution : GNSS, Map, Telecom signals, Opportunistic signals, …
 - estimating the instrument errors with augmented state equations



Hybridization with GNSS signals

| | Pros | Cons |
|------|--|--|
| GNSS | Bounded errors Self initialization | Lower attitude accuracy Vulnerable to interference, jamming Lower data rate |
| INS | Self contained Attitude estimation Higher data rate | Unbounded error growth Needs Initial state is needed |



© White Paper http://www.sappart.net/



Zero Velocity Update

- Biomechanics features in walking gait captured by foot mounted IMU (widely adopted)
- Main principle: during the stance phase, the foot velocity equals zero: $\dot{\mathbf{x}}^n = \mathbf{0}$
- Observation Equations
 - $-\delta$ is the perturbation of the state

$$-\begin{bmatrix}0\\\delta\dot{\mathbf{x}}^{n}\end{bmatrix} = \mathbf{q}_{b}^{n} \circ \begin{bmatrix}0 & (\mathbf{f}^{n} - \mathbf{b}_{f}^{n})^{T}\end{bmatrix}^{T} \circ (\mathbf{q}_{b}^{n})^{-1}\delta t + \begin{bmatrix}0\\\mathbf{g}^{n}\end{bmatrix}\delta t$$
$$-\begin{bmatrix}0\\\delta\mathbf{x}^{n}\end{bmatrix} = \dot{\mathbf{x}}^{n}\delta t + \frac{\mathbf{q}_{b}^{n}}{2} \circ \begin{bmatrix}0 & (\mathbf{f}^{n} - \mathbf{b}_{f}^{n})^{T}\end{bmatrix}^{T} \circ (\mathbf{q}_{b}^{n})^{-1}\delta t^{2} + \begin{bmatrix}0\\\mathbf{g}^{n}\end{bmatrix}\delta t^{2}$$

 Following the same strategy, Zero Angular Rate Update has been proposed





Mature Technologies ?

- With "body fixed" sensors
 - on foot (smart insole), waist, trunk
 - the closest to foot motion, the better
- Biomechanics for calibration
 - Stance phase (Foot)
 - Zero Velocity Update (ZUPT)
 - Zero Angular Rate Update (ZARU)
 - Trunk Roll Constraint
- Aiding ۲
 - Principal Building Directions
 - Visual Odometry/Gyro
 - Magnetometer Gradient





www.veristride.com



www.geonaute.com



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Overview and motivation

Background on strapdown inertial navigation system (INS)



Dead Reckoning with Handheld IMU



- Hand motion can hide global pedestrian locomotion
- "Strapdown" Mechanization cannot be applied
 - Algo. (freely carried devices) can take several forms
 - Sensors & context dependent
- Common Assumption
 - The user is watching the screen while walking
 - 'body fixed' like case

Strapdown INS with Handheld IMU

- Motion Lab
 - Multi-Camera tracking system with optical markers
 - Tree marker attached to the handheld IMU
 - High-accuracy
 - 60 Hz
- IMMU: inertial and magnetic mobile unit

 ADIS 16488





Strapdown INS with Handheld IMU

 5km/hr walk on a treadmill with texting and swinging hand

Texting Mode



Swinging Mode





Strapdown INS with "Texting" Hand



Strapdown INS with "Texting" Hand



Strapdown INS with "Texting" Hand

Vertical position Inertial estimation MotionLab Stride epochs Stride epochs Vertical(m) Error 310m after 2.5 min

Strapdown INS with "Swinging" Hand



Horizontal position estimation (GyInt)

Strapdown INS with "Swinging" Hand



Overview and motivation

Background on strapdown inertial navigation system (INS)

The challenge of personal navigation with handheld device



Review of Alternative INS Strategies

- Biomechanics of human walking gait
 - Repetitive steps
 - Assumed symmetry between right and left step
 - Upper body part contribute to the equilibrium
 - Repetitive arm motion during the displacement
- Alternative processing strategies
 - Different forms of algorithms (freely carried devices)
 - Sensors & context dependent
- Existing methods
 - Classification of activity and sensor carrying modes
 - Step/stride length modeling (no integration)
 - Sensor calibration with opportunistic signal (artificial magnetic field) or motion (quasi-static acceleration)
 - Hybridization with other sensors: camera, microphone, etc.

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Pedestrian Dead Reckoning



Walking Direction



Accurate Attitude Angles

Rotation

- Accurate attitude estimation is limited primarily by gyroscopes errors which can be controlled by
 - GNSS updates
 - New sensor configuration
 - Magnetometer
 - Reducing the filter error propagation (quaternion space)
 - New sensors
 - Opportunistic IMU motion
 - Unknown sensor orientation relative to body/user



Error Modeling in Quaternion Set

Rotation



Magnetic Field Update

Rotation

- When local magnetic field is constant over Δ*t*:
 2 updates
 - QSF: all \mathbf{m}^n are equal
 - MARU: quaternions derived from the magnetic and gyroscope angular rates over Δt are the same



Acceleration Field Update

Rotation

 \mathbf{q}_{ω}

- When the acceleration is Constant, over Δ*t*: 2 updates
 - QSF: all an acc. are equal
 - AGU (Acceleration Gradient Update): the quaternions derived from the gyroscope and the QSF acceleration should be the same

Renaudin et al., MAGYQ Based Attitude Estimation with Smartphone Sensors for Indoor Pedestrian Navigation, Sensors, 2014.



MAGYQ with "Texting" Hand

Velocity estimation



MAGYQ INS with "Texting" Hand



MAGYQ INS with "Texting" Hand

Vertical estimation 90 80 70 Inertial estimation MotionLab Stride epochs 60 Stride epochs Vertical (m) 40 30 20 Error 90m after 2.5 min, before: 310m 10 Ω 20 60 80 0 40 100 120 140 Time(s)

MAGYQ INS with "Swinging" Hand



MAGYQ INS with "Swinging" Hand

Vertical position estimation (Magyq)



Human Gait Analysis



Motion and Carrying Mode Recognition



Input Space –

 $X = \begin{bmatrix} x_1, x_2, \dots, x_n \end{bmatrix}$

IMU Signal Features

Decision Rule:

 $X \to f(X) \to y_k \in Y$

mapping function

Classifier

Output Space

$$y_{k \in \{1,m\}} \in Y = [y_1, y_2, ..., y_m]$$

- Adapt the algorithms to the context to bound positioning error
- A classification problem
 - Pre-processing \rightarrow Feature extraction \rightarrow Decision Making

f(X)

- Motion states
 - User: Standing, Running, Walking, Up/Down Stairs
 - IMU/Hand: Phoning, Texting, Bag Carrying, Swinging, Irregular Motion



Selecting Features



Manifold features

- Energy
- Variance
- Standard deviation
- Frequencies in subbands
- STFT coefficients

Pattern Extraction

- Faster Motion modes migrate the signal energy toward highest frequencies (acc. signal)
- Periodic arm rotation induce frequency peaks (gyro signals)







Step Frequency Extraction



- Estimated independently from step detection: remove correlation in the filter, more robust
- Extraction of dominant frequencies with Short Time Fourier Transform (STFT) over 2 sec. sliding window
 - Three peaks
- Coupling problem of the strongest hand frequency with step or stride
 - Binary Detector based on biomechanics feature of walking gait



Defining a Model

Experimental approach with controlled walking pace

$$s = h(af_{step} + b) + c$$

- s: step length
- $\{a, b, c\} \in \mathbb{R}$: individual parameters set
- -h: the pedestrian's height



Evolutionary Gait

Step Length Model



- Walking Gait influenced by varying physiological conditions tiredness, injuries, carrying a bag, ...
 - Frequent calibration is needed
- Several approaches are possible depending on the application
 - Walking along a known footpath
 - Use departure / destination info
 - Hybridization with opportune signal (GNSS, WiFi, etc.)



Distance Estimation Performance

Step Length Model



- Calibration using GNSS Doppler
 - 10 sec. PDR/GPS Doppler hybridization
 - 2% mean error over 700m with 4 test subjects with freely carried device (texting, swinging)

Renaudin et al., Adaptative Pedestrian Displacement Estimation with a Smartphone for Free Inertial Navigation, IPIN, 2013.





Renaudin et al., MAGYQ Based Attitude Estimation with Smartphone Sensors for Indoor Pedestrian Navigation, Sensors, 2014.

MAGYQ + PDR


Estimating the Walking Direction



Deformable Model



- Features extraction from the accelerations dataset, in navigation frame, over a step
- Fundamental assumptions
 - *H*: Pedestrian Gravity
 Center dynamic is
 observable
 - *H2*: Acceleration in the navigation frame are unbiased





Three Strategies

IMU misalignment

- Principal component analysis of the accelerations
 - *Algo:* find the direction of the horizontal oscillations in the estimated acceleration
 - *H*: constant misalignment over a step (even several)
- « Pattern Matching » on a reference acceleration signal signature in the forward and lateral directions
 - *Algo:* minimize of the distance between the pre-determined shape and the estimated acceleration
 - *H*: availability and validity of a universal model walking model
- Frequency analysis of inertial signals inspired by biomechanics
 - *Algo:* find the direction of oscillations by using the periodicity of the human walking
 - *H*: robust gait analysis is possible



Common Elements

IMU misalignment

• Pre-processing

- Estimation of the IMU's attitude angles
- Estimation of the IMU's acceleration: removing the gravity component
- Biomechanics Outcomes
 - The motion of the pedestrian's center of mass is cyclic
 - Analysis can be conducted over several steps or stride



Principal Component Analysis (PCA)

Observations

- Variance of horizontal acc. is maximum along the forward direction
- Variance of horizontal acc. is minimum along the lateral direction
- Problem statement
 - find the horizontal unit vector **u** that maximizes $\max_{\|\mathbf{u}\|=1} \left(\sum_{i=1}^{n} \langle \mathbf{u}, \ddot{\mathbf{x}}_{H}(i) \rangle^{2} \right)$



IMU misalignm<u>ent</u>





Forward and Lateral Acc. Modeling (FLAM)

IMU misalignment

- Assumption
 - Forward and Lateral acc. models over a stride/step exist

$$\ddot{\mathbf{x}}_m(t) = \sum_{i=1}^n \ddot{\mathbf{x}}_H \sin(tb_i + c_i)$$

- Problem statement
 - Find θ that maximizes the correlation

$$\max_{\theta} \sum_{i} \ddot{\mathbf{x}}_{m}(i) \left(\ddot{\mathbf{x}}_{H}^{T}(i) \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix} \right)$$

- Waking direction θ is the weighted sum of the 2 angles found for the 2 models





Frequency analysis of Inertial Signals (FIS)

IMU misalignment

Observation

- The energy of the signal is maximum along the forward direction at step/stride frequency
- Problem statement
 - Find θ that maximizes the spectral density of the acc. and gyro. signals energy at step/stride frequency
 - Acc. and gyro freq. and phase components $\ddot{X}(\omega)$ and $W(\omega)$ estimated by STFT
 - Compute forward and lateral power spectral densities (P_{Xf}, P_{Xl}) and (P_{Wf}, P_{Wl})
 - $-\max_{\theta}(w_1 P_{\ddot{X}f}(\theta) + w_2 P_{\ddot{X}l}(\theta) + w_3 P_{Wf}(\theta) + w_4 P_{Wl}(\theta))$



Comparative Analysis



• Overall experimental results in Motion Lab (see previous videos)

- Swinging mode : error < 10°
- Texting mode: mean error < 30°



PCA

- sensitive to oscillations

FLAM

- need a large database
- IMU carrying mode dependent
- Person dependent (gender, weight, etc.)

FIS

- globally more robust
- Gat Analysis dependent
- Accuracy is not sufficient



Combettes et al., Comparison of misalignment estimation techniques between handheld device & walking directions, IPIN, 2015.

Overview and motivation



Personal Inertial Navigation System with Handheld Devices is becoming a reality

Opens the way to new research fields

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