Effective approaches for error mitigation during IMU-based assessments of human movement: Recommendations from expert focus groups

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Summary

This work summarizes the findings from an expert focus group study aimed at eliciting effective approaches for error mitigation during human movement assessments using inertial measurement units (IMUs). An error classification framework was refined and validated, high-risk sources of error were identified, and recommendations for development of universal best practice guidelines were provided.

Introduction

The use of IMUs for assessments of human movement is becoming more ubiquitous, in part due to the lower cost and ability to collect data outside of traditional biomechanics labs. Despite the potential advantages, inherent limitations with the technology have potential to negatively impact data quality if not handled appropriately, which lowers research credibility and limits the full exploitation of IMUs to highly qualified personnel. There is an increasing demand for a consensus on standard procedures for obtaining valid and reliable outcomes to strengthen the quality of the rapidly-growing body of IMU-based research. The objectives of this study were to: 1) refine and validate a previously developed error classification framework [1], 2) provide initial recommendations for error mitigation, 3) conduct an error risk assessment, and 4) identify directions for future development of universal best practices.

Methods

Nine IMU experts from around the world participated in four virtual focus groups aimed at eliciting effective approaches for error mitigation. Focus groups were conducted via video-conferencing (Zoom, USA), and facilitated via an interactive whiteboard (Miro, USA). Data collection continued until thematic code saturation was reached (i.e., no new information was identified and further data collection became redundant), and a deductive thematic analysis approach was used. Participants then ranked the probability and severity of potential errors on a scale from 1-5 to evaluate error risk.

Results and Discussion

The error classification framework in [1] was refined as per participant feedback (Figure 1), and effective approaches for reducing measurement uncertainty and mitigating error were provided for 36 sources of error. There was a large emphasis on setup errors and a small emphasis on noise errors, which suggests that there are high-quality IMU technologies readily available, such that users are more concerned about *how* the technology is used rather than the technology itself. Careful consideration should be given to identified high-risk and highly variable sources of error, as recommendations for best practice are likely to vary based on individual experimental protocols. Several broader themes emerged, which cover: context-specific considerations, IMU specifications, intended end-user/-goal, and challenges in developing universal best practices that cover the breadth of research interests.

Table 1: Mean (SD) error probability, severity, and overall risk (risk = probability × severity) for high-risk sources of error (*), as well as errors with highly variable probability (†) and severity (‡) scores.

Source of error	Probability	Severity	Risk
Rate random walk*	4.4 (0.9)	4.4 (1.2)	17.8 (10.0)
Angle random walk*‡	4.3 (1.2)	4.4 (1.2)	17.4 (10.4)
Rate ramp*	4.4 (1.1)	4.3 (1.4)	17.4 (10.4)
System crash†	2.2 (1.5)	4.0 (1.2)	9.8 (8.1)
Bias temperature sensitivity†	2.9 (1.5)	2.8 (1.5)	9.2 (9.2)
Storage capacity†	2.0 (1.5)	3.2 (1.4)	7.6 (8.0)
Powerline interference†‡	2.0 (1.5)	2.2 (1.7)	5.8 (8.0)
Quantization noise‡	3.7 (1.4)	3.3 (1.8)	13.2 (10.2)
Electronic noise‡	3.3 (0.9)	2.9 (1.7)	9.7 (5.9)

Conclusions

The recommendations presented in this work may serve as a resource to ensure all sources of error are considered during study design, implementation, analysis, and reporting. Further development of best practice guidelines is recommended.

References

[1] Beange KHE et al. (2023). *IEEE MeMeA '23 Proc.*, 1-6.

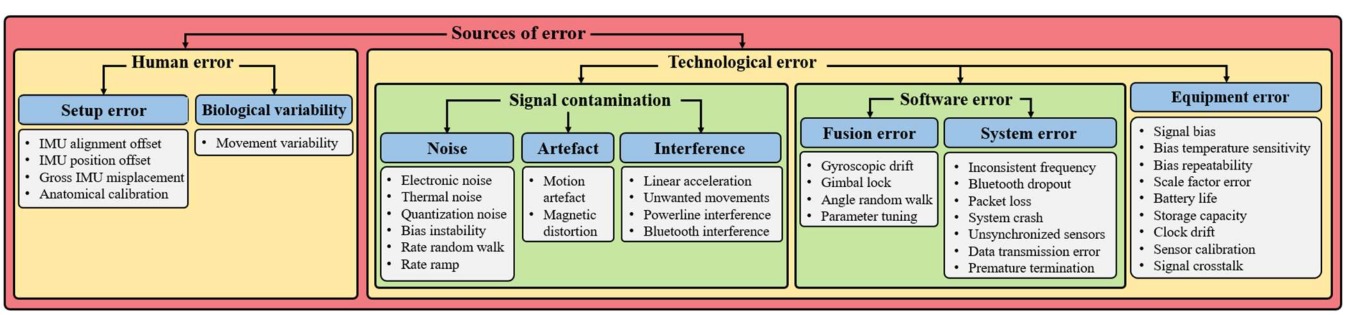

Figure 1: Error classification framework, updated from [1].