## Multi-sensor integration and data fusion for enriching gait assessment In and Out of the laboratory

**A. Cereatti**[1,2], S. Bertuletti[1,2], M. Caruso[3], F. Salis[1,2]
[1]Department of Biomedical Sciences, University of Sassari, Italy; [2]IUC-BOHNES, Italy; [3]Department of Electronics and Telecommunications, Politecnico di Torino, Italy
Email: acereatti@uniss.it

### Summary

**This paper deals with the design of a wearable multi-sensor system (INDIP) that exploits a synergistic integration of different sensor types to provide a "best available" solution for digital gait assessment in real world scenarios.**

### Introduction

Recently, there has been a growing interest among movement experts in methods for monitoring individual motor performance during daily-life activities. To this end, miniaturized inertial unit (MIMU) turned out to be the most relevant technological solution. From direct measures of angular velocity and proper acceleration of given body segments, a broad set of spatio-temporal gait variables can be derived through signals morphology analysis, the use of biomechanical models and machine learning techniques. However, validity of IMU-based methods greatly depends on several factors (motor impairment severity, environmental context, MIMU position). Furthermore, due to drift integration, accurate displacement estimations can be particularly critical. Full acceptance of IMU-based methods for "real world" mobility assessment in clinical programmes needs a rigorous validation and this, in turn, advocates for the development of gold standards. This paper deals with the design of a wearable multi-sensor system (INDIP) that, by means of a synergistic integration of different sensor types, aims to provide a "best available" reference for digital gait assessment in real world scenarios.

### Methods

The system includes in its full bilateral configuration: 2 magneto-IMU ($f_s$=2kHz), 4 distance sensors (DSs) (range=0.6m, $f_s$=50Hz) and 2 plantar pressure insoles (16 sensing elements, $f_s$=100Hz) positioned as depicted in Fig.1a.

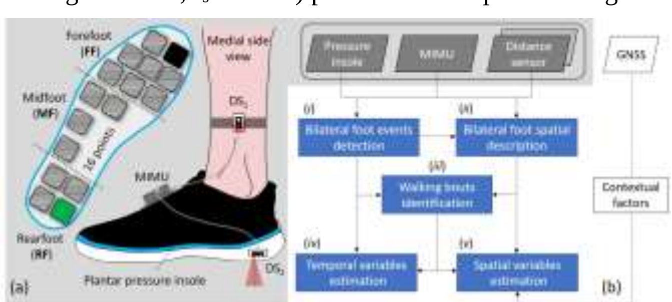


**Figure 1**: Overview of hardware/algorithm architecture.

Data are acquired by an ultra-power microcontroller and synchronized through BLE protocol. The system includes a flash storage for data logging (up to 4h) and it can receive analog triggers for synchronization with third-party devices. A workflow of the data processing is illustrated in Fig.1b and includes: *(i)* bilateral description of temporal events at foot level. This operation primary relies on pressure data and secondary on inertial and distance data; *(ii)* description of the foot position and orientation. This operation mainly relies on inertial data. Gait cyclicity is exploited to implement zero velocity update techniques and self-tuning sensor fusion algorithms for reduction of the integration drift errors [1]; *(iii)* walking bouts identification based on information provided in (*i, ii)* and according to standardized operational definitions; (*iv, v*) estimation of spatio-temporal gait variables for different walking bouts lengths.

### Results and Discussion

Multi-sensor selection was operated to take full advantage of complementary characteristics of each sensing technology to obtain a richer set of information that can drive and enhance gait assessment. For instance, by exploiting the 16-element pressure readings, it is possible to differentiate initial and final contacts for the different foot subareas ($IC_{RF}$, $IC_{FF}$, $FC_{RF}$, $FC_{RF}$) (Fig.1a, Fig.2). This allows to achieve a finer gait cycle segmentation compared to IMU-based methods only. Thanks to the use of DSs, foot displacements, as estimated from the inertial data, can be supplemented with information on foot clearance and inter-shank distance (Fig.2). These data can prove useful when analysing highly abnormal gait patterns (e.g. foot-dragging walks, freezing).

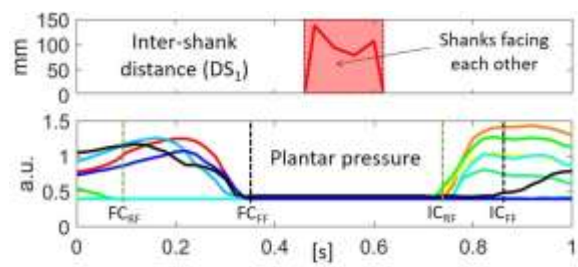


**Figure 2**: An example of $DS_1$ and plantar pressure data during gait.

As supervised single-sensor machine learning methods require good labelled data, the INDIP system can also be used for generating reliable training data set. Finally, geolocation techniques can be easily integrated via BLE to correlate gait variables with contextual factors (Fig.1a).

### Conclusions

Through the integration and synergistic use of different type of sensors, INDIP has the potentiality to achieve more robust, accurate and complete gait assessment.

### Acknowledgments

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### References

[1] Trojaniello et al. (2014) *JNER*, **11**:152.
[2] Bertuletti et al. (2019), *JoB*, **84**: 274-277.