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Adding accelerometry raises task-conditioned recoverability in wearable photoplethysmography

Maurice Antony Ewing

mewing4@uic.edu

University of Illinois at Chicago https://orcid.org/0009-0005-1550-1718

Research Article

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Adding accelerometry raises task-conditioned recoverability in wearable photoplethysmography

M. Antony Ewing, PhD
Conquer Medical Health
ORCID: 0009-0005-1550-1718
Correspondence: mae@conquermedical.health

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Abstract

Wearable photoplethysmography (PPG) is easy to collect, but its downstream value depends on whether the recorded signal preserves the distinctions required by the inference task. This study tests whether task-conditioned recoverability separates model limitation from measurement limitation and whether an added physical sensor increases recoverable information. The analysis uses the Brno University of Technology Smartphone PPG Database v2.0.0 and contains 82,966 balanced ECG-QRS event/non-event samples from 3,840 recordings and 38 subjects. A compact machine-learning model zoo comprising logistic regression and histogram gradient boosting establishes demonstrated subject-held-out performance; cross-subject nearest-neighbor geometry over prespecified representations supplies a comparative recoverability estimate. PPG alone yields balanced accuracy of 0.5018 and recoverability of 0.5454. Expert-rated good recordings yield higher recoverability than expert-rated poor recordings (0.5706 versus 0.5488), with the same ordering in all eight perturbation conditions. On the same ACC-capable records, adding accelerometry raises recoverability from 0.5520 to 0.6148 and balanced accuracy from 0.5007 to 0.5957. The recoverability quantity is comparative and task-conditioned. The results show that changing the physical measurement can change both the performance an observer reaches and the information available for the declared task.

1 Introduction

Photoplethysmography measures changes in detected light produced by blood-volume changes in tissue. Phones and wearable devices can collect PPG inexpensively, but motion, contact pressure, ambient light, peripheral perfusion, and related disturbances can alter the waveform [1, 2]. Accelerometers can help characterize motion, and signal-quality indices can identify degraded recordings [3, 4]. These tools address signal quality and artifact burden. A different question arises when a downstream predictive model performs poorly: did the model fail to extract usable information, or did the measurement fail to preserve enough task-relevant information in the first place?

Those two explanations imply different actions. Model limitation calls for a better observer, representation, calibration strategy, or training procedure. Measurement limitation calls for a better acquisition, a different sensor configuration, an added modality, or a decision to withhold the inference. Predictive accuracy alone cannot separate these cases because the observed score combines properties of the measurement with properties of the fitted model.

OptiCeil separates demonstrated held-out performance from comparative task-conditioned recoverability. For a declared sensor representation and target, the architecture reports the performance reached by tested observers and estimates how much performance remains recoverable across prespecified representations and geometries. A stronger held-out observer can falsify a candidate recoverability estimate. The resulting quantity is an empirical, representation- and validation-conditioned diagnostic with a different scope from an absolute physical limit.

The BUT PPG database provides a direct external test because it pairs smartphone PPG with ECG reference data, accelerometry, expert signal-quality labels, and controlled perturbations [5, 6]. The analysis asks two primary

questions. First, do expert-rated good recordings support greater task-conditioned recoverability than expert-rated poor recordings? Second, on the same records, does adding accelerometry increase both achieved performance and the recoverability estimate? The second comparison isolates a change in the physical measurement system while holding the record set fixed.

2 Methods

2.1 Dataset and task

The analysis uses BUT PPG v2.0.0 [5]. The frozen event substrate contains 82,966 balanced ECG-QRS event/non-event examples from 3,840 recordings and 38 subjects. Forty-eight legacy records are absent from the event substrate produced by the frozen extraction. Their absence precedes outcome analysis and model evaluation. Each example uses a 0.20-s pre-event and 0.80-s post-event window resampled to 100 Hz, with at most 12 positive events per record.

The target distinguishes PPG windows centered on ECG-QRS reference events from matched non-event windows. Subject identity defines the unit of independence, so one person's samples remain within a single fold.

2.2 Machine-learning observers and task-conditioned recoverability

Subject-grouped fivefold cross-validation evaluates a compact machine-learning model zoo containing logistic regression and histogram gradient boosting. The strongest held-out balanced accuracy among these observers defines demonstrated performance for each analysis. The recoverability calculation separately evaluates one-nearest-neighbor error in held-out subjects across standardized raw and principal-component representations, together with score-space representations, and uses the Cover-Hart relation to transform nearest-neighbor error into candidate recoverability values [7].

The procedure treats candidate recoverability values as falsifiable empirical quantities. Any candidate lying below a stronger held-out observer beyond the frozen tolerance is removed. The largest surviving candidate defines the reported comparative recoverability estimate for the declared representation family. The difference between recoverability and achieved balanced accuracy is reported as a descriptive tested-geometry gap.

2.3 External quality and sensor-value checks

BUT PPG provides expert quality annotations independent of the ECG-QRS event target. The analysis compares expert-good and expert-poor recordings overall and within coughing, finger movement, laughing, light change, pressure, rest, talking, and walking conditions.

The sensor-value analysis repeats the same event task on the identical ACC-capable record subset using PPG alone and PPG plus accelerometry. This paired design tests whether an added physical channel changes the information available for the same declared task.

3 Results

3.1 PPG alone provides limited cross-subject ECG-QRS recoverability for this task

Across all 82,966 balanced samples, the strongest held-out observer reaches balanced accuracy of 0.5018. The surviving comparative recoverability estimate is 0.5454, giving a tested-geometry gap of 0.0436. Under this specific balanced ECG-QRS recovery task and subject-grouped validation design, the tested smartphone PPG representation supports little cross-subject discrimination above chance. This finding is task-specific; PPG can remain informative for other cardiovascular targets and representations.

Table 1: Primary OptiCeil results. Gap is the descriptive difference between comparative recoverability and achieved balanced accuracy.

Analysis	Samples	Achieved BA	Recoverability	Gap
Overall PPG	82,966	0.5018	0.5454	0.0436
Expert good	16,776	0.5087	0.5706	0.0618
Expert poor	66,190	0.4998	0.5488	0.0490
PPG only, ACC-matched	82,966	0.5007	0.5520	0.0513
PPG + ACC, same records	82,966	0.5957	0.6148	0.0191

3.2 Expert-rated quality tracks task-conditioned recoverability

Expert-good recordings support recoverability of 0.5706, compared with 0.5488 for expert-poor recordings. Achieved balanced accuracy is 0.5087 and 0.4998, respectively. The recoverability ordering holds within all eight controlled perturbation conditions. The separation is largest during laughing (0.737 versus 0.625) and pressure (0.744 versus 0.625) and smallest at rest (0.576 versus 0.560). Because the expert label is independent of the QRS event target, this comparison provides an external check on the measurement-facing diagnostic.

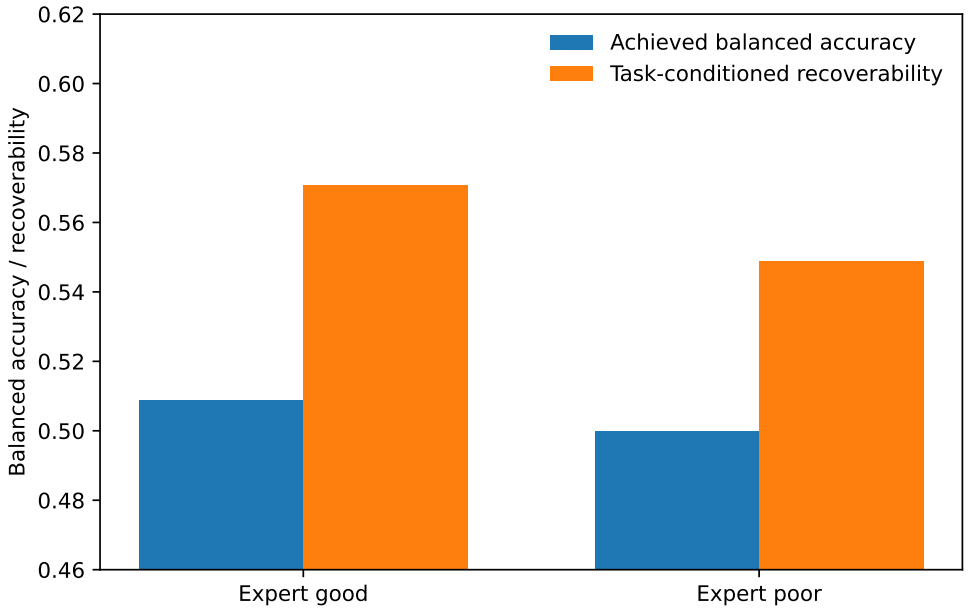


Figure 1: Independent expert-quality check. Expert-good recordings support higher task-conditioned recoverability than expert-poor recordings.

3.3 Adding accelerometry raises task-conditioned recoverability on the same records

On the identical ACC-capable record set, PPG alone yields recoverability of 0.5520 and achieved balanced accuracy of 0.5007. Adding accelerometry raises recoverability to 0.6148, a gain of 0.0628, and raises achieved balanced accuracy to 0.5957, a gain of 0.0950. The descriptive gap contracts from 0.0513 to 0.0191.

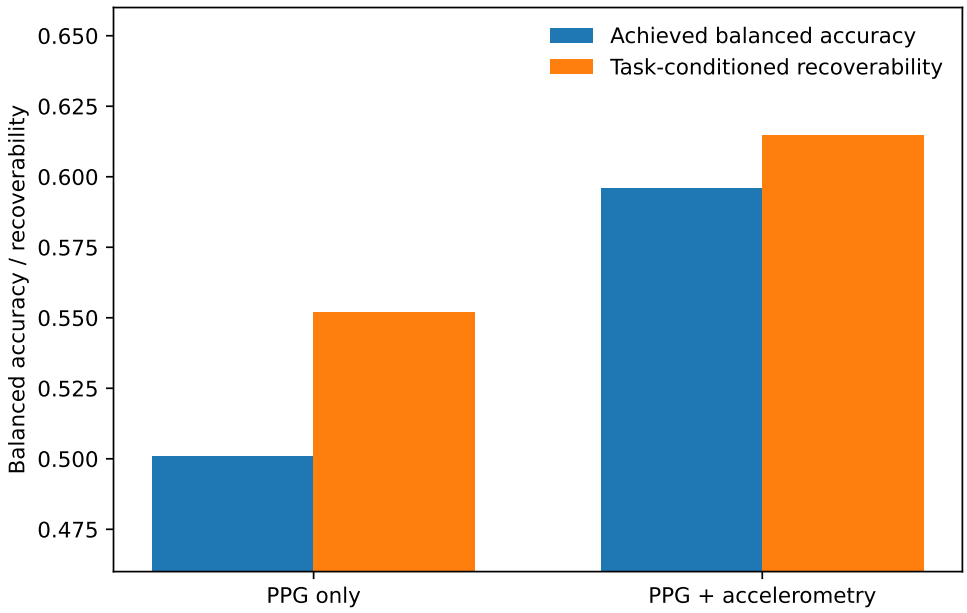


Figure 2: Sensor-value test on identical records. Adding accelerometry raises both achieved balanced accuracy and task-conditioned recoverability.

This comparison changes the physical measurement system while preserving the evaluation records and target. Both the observer result and the measurement-facing diagnostic move with the added channel.

4 Discussion

PPG research has developed extensive methods for artifact removal, signal-quality assessment, and robust physiological tracking [1, 2, 3, 4]. OptiCeil addresses the measurement question upstream of ordinary model comparison: how much task-relevant information does the tested measurement preserve, and how much of that information do current observers reach?

The BUT PPG results answer that question in two ways. Expert-good recordings support higher recoverability than expert-poor recordings overall and within every controlled perturbation condition. The expert labels come from an independent quality assessment, so the ordering links the recoverability estimate to an external property of the measurement. The accelerometry experiment provides the stronger sensor-design test. On identical records, the added physical channel raises recoverability by 0.0628 and achieved balanced accuracy by 0.0950. A measurement change moves the task-conditioned information state as well as the score reached by the fitted observer.

The achieved-performance/recoverability pair also clarifies the next engineering action. A comparatively high recoverability estimate with lower achieved performance points toward observer development, representation learning, calibration, or domain adaptation. Low values for both quantities point toward acquisition. The available actions can include improving contact, repeating the recording, changing the observation window, adding a sensor, or withholding the target inference until the measurement improves.

The low PPG-only values apply to ECG-QRS event recovery under this specific representation and subject-held-out design. ECG-QRS marks an electrical cardiac event, while smartphone PPG records a peripheral optical pulse shaped by electromechanical delay and vascular transmission. Pulse-rate estimation and other PPG tasks can occupy a different information regime. Task conditioning is central to the interpretation.

The recoverability estimate remains finite-data and representation-conditioned. Its role is comparative and falsifiable: a stronger held-out observer invalidates a lower candidate estimate. Prospective sensor validation, natural-prevalence clinical testing, and physical device optimization remain separate experimental questions.

5 Limitations

The evidence comes from one retrospective public database with a fixed set of subjects, phones, acquisition conditions, and perturbations. The frozen event substrate contains 3,840 records and excludes 48 legacy records absent from that extraction. Expert quality labels provide an external measurement check but not a physiological gold standard. The nearest-neighbor transformation relies on asymptotic theory, and the reported recoverability estimate spans only the tested representation family. The balanced event/non-event design measures controlled discrimination rather than clinical-prevalence diagnostic accuracy.

6 Conclusion

Wearable PPG performance reflects both model capacity and measurement content. In BUT PPG, expert-good recordings support greater task-conditioned recoverability than expert-poor recordings, and adding accelerometry on the same records raises both achieved balanced accuracy and comparative recoverability. The paired result makes the practical distinction concrete: changing the model and changing the measurement are different interventions, and a measurement-facing recoverability diagnostic can help determine which one the task requires.

7 Data and code availability

The BUT PPG v2.0.0 data are publicly available from PhysioNet [5]. The public OptiCeil software repository, evaluation SDK, validation summary, and interactive demonstrator are available at `https://github.com/ConquerMedical/OptiCeil` and `https://conquermedical.github.io/OptiCeil/`. The public release exposes frozen aggregate validation results and evaluation interfaces. Production recoverability estimation, calibration internals, geometry search, acquisition ranking, and private validation pipelines remain outside the public release.

8 Intellectual property disclosure

Relevant methods and computational systems are the subject of previously filed United States provisional patent applications. This manuscript discloses the mathematical objects, empirical definitions, validation logic, and results necessary to evaluate and reproduce the reported scientific analyses. Proprietary operational implementations and system components unnecessary for reproduction of the reported analyses remain outside the scope of disclosure. Publication of this manuscript grants neither a patent license nor a commercial software license.

9 Competing interests

The author is Founder of Conquer Medical Health and has financial and intellectual-property interests in OptiCeil, TopolAI, and related computational systems. Relevant methods and systems are patent pending. The author declares no other competing interests.

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This study received no external funding.

11 Author contributions

M.A.E. conceived the study, developed the framework, designed and conducted the analyses, interpreted the results, and wrote the manuscript.

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