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Using Body-worn Accelerometers to Detect Physiological Changes During Periods of Blast Overpressure Exposure

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Abstract— **Repetitive exposure to non-concussive blast exposure may result in sub-clinical neurological symptoms. These changes may be reflected in the neural control gait and balance. In this study, we collected body-worn accelerometry data on individuals who were exposed to repetitive blast overpressures as part of their occupation. Accelerometry features were generated within periods of low-movement and gait. These features were the eigenvalues of high-dimensional correlation matrices, which were constructed with time-delay embedding at multiple delay scales. When focusing on the gait windows, there were significant correlations of the changes in features with the cumulative dose of blast exposure. When focusing on the low-movement frames, the correlation with exposure were lower than that of the gait frames and statistically insignificant. In a cross-validated model, the overpressure exposure was predicted from gait features alone. The model was statistically significant and yielded an RMSE of 1.27 dB. With continued development, the model may be used to assess the physiological effects of repetitive blast exposure and guide training procedures to minimize impact on the individual.**

Clinical Relevance—**This paper provides evidence to suggest that there is signal in body-worn accelerometry that indicates changes in gait across periods of repetitive exposure to blast overpressures. Further investigation is needed to understand the extent of the impact of repetitive overpressure exposures on the brain.**

I. Introduction

In the military and law enforcement, individuals may be exposed to occupational blast overpressure, which is the shock wave from the blast that is over normal atmospheric pressure. Specifically, "breachers" are those who use explosives to gain entry into a building or room. For tactical reasons, these breachers typically deploy the explosives in close proximity to expedite their movement. The majority of exposures are at a putative sub-clinical level, meaning that right after the blast, there is no diagnosable injury stemming from that blast exposure. The eventuality then is repetitive exposures to overpressures with little immediate measurement of the neurophysiological impact.

Recent studies have drawn links between overpressure exposure and sleep disturbances, short- and long-term neurocognitive declines [1–3], emotion regulation [4], hearing function [5,6], headaches [7], and vestibular function and balance [8]. Chronic overpressure exposure has been shown to yield symptomology similar to concussions, which has an impact on the individual's daily activities [9]. Adding to the complexity of the studies is the individual physiological variability and differences in effects seen across populations.

A consistent component of the diagnosis of blast-related brain injury is the presence of balance and gait impairment [10,11]. In the laboratory and clinic, balance and gait are assessed using a combination of treadmills, force plates, and motion capture [12,13]. In naturalistic conditions, body-worn accelerometers can provide insight into changes in gait dynamics [14,15].The added benefit of wearable accelerometers is the capability for continuous, long-duration data collection while individuals performed their regular activities.

In the present study, on-body accelerometry was collected on breachers as they performed their training activities. Similarly, the cumulative level of overpressure exposure was collected using on-body dosimeters. The results demonstrate the potential for a capability to continuously monitor the levels of exposure and quantify the effects on changes in gait and balance. The focus of the current analysis is on characterizing the physiological effect, as assessed through changes in accelerometer-based features, of overpressure exposure.

II. Methods

A. Study Participants

Service members in the U.S. Army Special Operations Command (USASOC) and Special Agents in the Federal Bureau of Investigation (FBI) train with explosives as part of their occupation. During their period of training, data from on-body overpressure dosimetry and head-mounted accelerometry were collected for the duration of the period of blast exposure. The dataset comprised 44 different recording sessions, which included 16 unique individuals, 12 days of recording, and 2 field sites. Data collection procedures were approved by the MIT Committee on the Use of Humans as Experimental Subjects, the Air Force Human Research Protections Office, and the FBI Institutional Review Board.

B. Overpressure Dosimetry

Overpressure dosimetry was achieved through the continuous recording of acoustic pressures during the training period. A G.R.A.S 47BX-S7 (GRAS Sound & Vibration A/S, Holte Denmark) pressure microphone with a peak sound pressure level of 184 dB SPL was mounted on the non-firing shoulder facing upwards. USASOC data were collected using a commercial audio recorder, the TASCAM DR-100mkIII (TEAC, Montebello, CA), as detailed in [16]. The FBI overpressure data were collected with the same G.R.A.S microphones and a prototype recorder [17] that only stored

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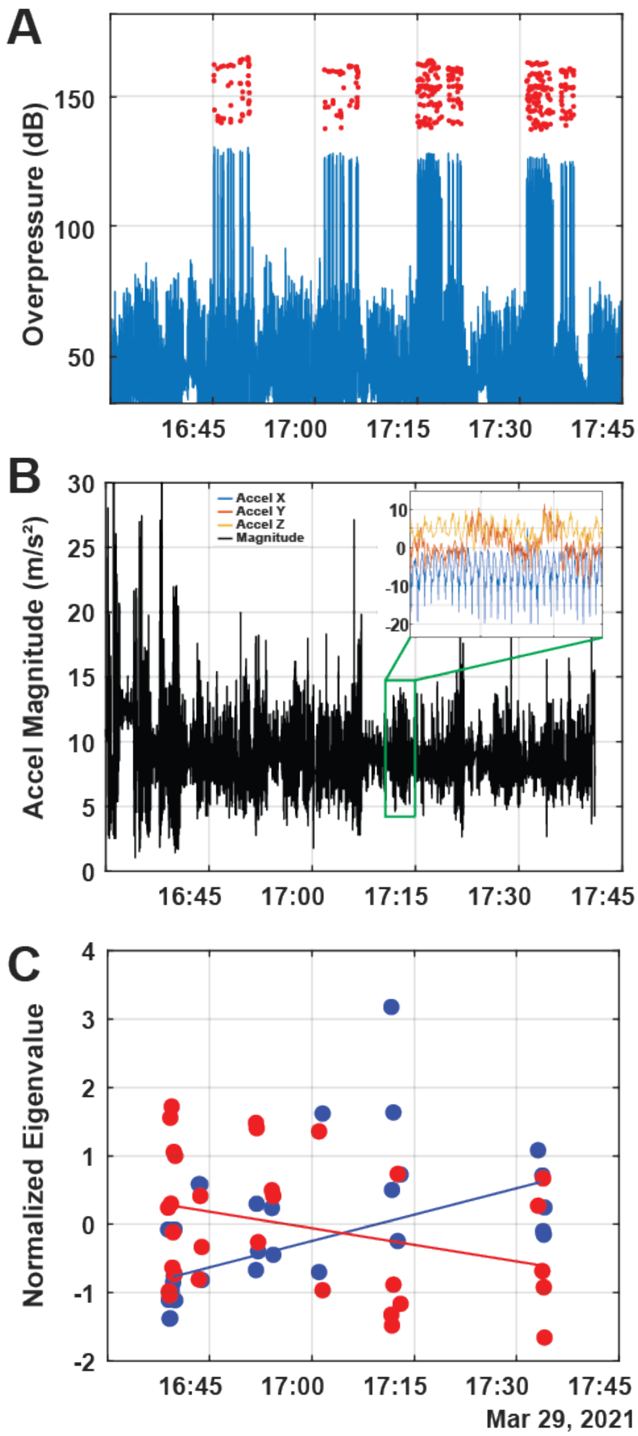

Fig. 1. Representative monitoring of overpressure and on-body accelerometry during periods of blast exposure. A) Continuous sound and pressure data (*blue*) are averaged in $100ms$ windows. Peak overpressure events are denoted in red. B) Three-axis accelerometry data, recorded on body, were converted to a magnitude signal (*black trace*). As an example of detected periods of gait, the inset shows the raw accelerometry data for a short period of time. C) Two representative eigenvalue features (rank 1 in *blue*, rank 8 in *red*) are shown for the periods of detected gait. The rank 1 feature shows positive trend through the periods of overpressure exposure and the rank 8 feature shows a negative trend.

impulse pressure waveforms. The U.S. military standards for noise exposure, in MIL-STD-1474E, are quantified using an 8-hour equivalent A-weight impulse noise level – L_{Aeq8hr}. As such, we report exposure data in similar fashion.

C. Accelerometry Signal Acquisition

On-body accelerometry data were collected using a Shimmer3 ECG/EMG unit (Realtime Technologies Ltd, Dublin, Ireland). The accelerometer had 14-bit resolution, was set to a range of $\pm 8g$, and has RMS noise reported at $0.6mg$ [18]. The sampling rate was 512 Hz. Accelerometers were mounted to the helmets of the participants typically via Velcro or tape. Accelerometry data were collected for 29 participants across several days for a total of 98 unique data collections. The 98 cases were narrowed down to 44 that each had sufficient, associated dosimetry collection.

D. Gait & Low-Movement Segmentation

Accelerometry data was segmented into time periods with gait and low-movement (LM) to distinguish changes over time in head movements that occur during ambulation from those that occur during periods of standing or sitting. Similar methods of activity-based segmentation have been used previously to measure movement abnormalities due to Parkinson's disease [19] and exertional heat stroke [20]. Primary considerations for Gait and LM segmentation are built upon methods established in this prior work.

The acceleration magnitude at each time point is the square root of the sum of the squares of accelerations in the three axes. Segmentation of each activity type occurs when the standard deviations of these acceleration magnitudes, computed across an overlapping, sliding 10 s window, $\sigma_m(t)$, with a step size of 1 s, are sustained at certain levels. The first activity type, Gait, is initially segmented based on time periods in which $\sigma_m(t) > 0.17$, across a $30s$ interval, with a tolerance for short subthreshold gaps of $15s$ or less duration, for added leniency.

The second behavior type, LM, is represented by segments containing contiguous values of $0.03 < \sigma_m(t) < 0.1$, again across a $30s$ interval. These thresholds constrain activity to a lower magnitude of acceleration variance representative of the low-movement activities of standing or sitting.

The initial segmentation described above is followed by selection of 5 s frames for further feature processing in Section II-E. For gait frames, there is an additional periodicity test to ensure sufficient consistency of gait, in order to ensure high quality gait features, as follows. The first principal component of the three accelerometry axes in the 5 s window is computed. Next, the autocorrelation peak within a one second time delay is required to have a peak prominence of at least 0.6 for the 5 s frame to be included for processing in Section II-E. All contiguous 5 s frames within LM segments are included for processing in Section II-E.

E. Correlation Structure Features

We hypothesized that movement dynamics would change in relation to blast exposure and time in Gait and LM periods

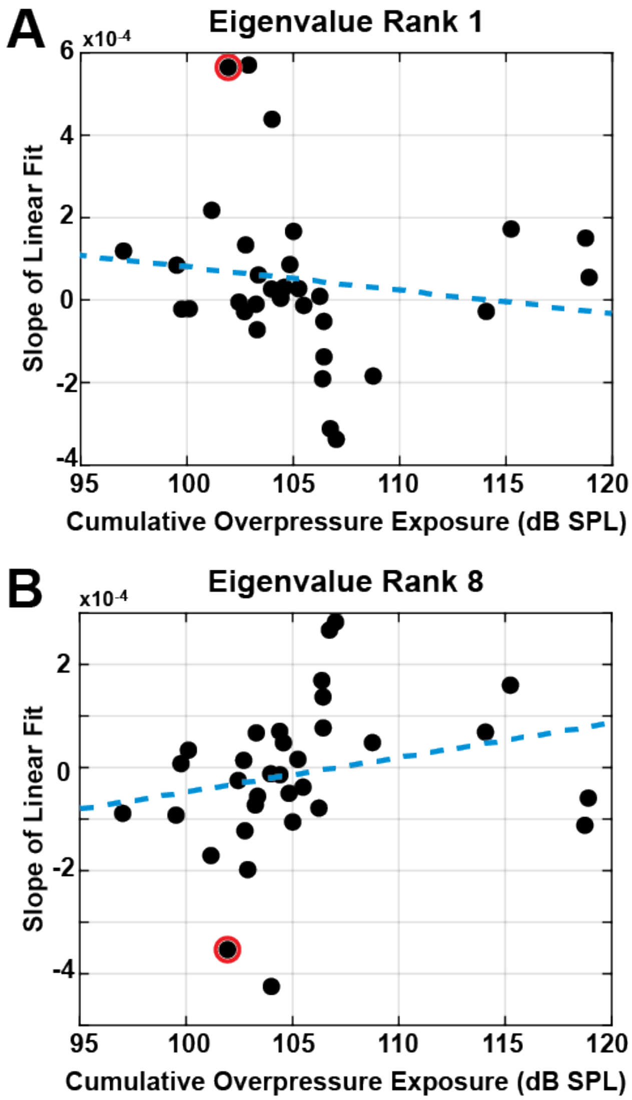

Fig. 2. Trends in eigenvalue features are plotted as a function of overpressure exposure. The ordinate of each data point represents the slope of the eigenvalue feature across the entire period of blast exposure in a single session, and the abscissa is the cumulative level of overpressure exposure for that session. The example data shown in Fig. 1C are highlighted as the data point in red. A) For the rank 1 eigenvalue, the negative trend (*blue dashed line*) indicates that, for higher levels of exposure, the gait-related eigenvalue feature tend to have a more negative slope across the session. The correlation between the rank 1 eigenvalue feature slope and blast exposure is -0.29. B) Conversely, for the rank 8 eigenvalue, the greater the exposure, the more positive the eigenvalue feature slope tends to be. The correlation between the rank 8 eigenvalue feature slope and blast exposure is 0.46.

- the former detected by a high magnitude and stable periodicity of head movements, and the latter identified where average magnitude of head movements is relatively small. For a particular range of movement frequencies, movement dimensionality can be quantified by the fraction of total movement variance that is explained by correlations between acceleration signals across a particular set of relative time delays.

A general approach has been developed that quantifies movement dimensionality in this way, using correlation patterns among multichannel feature sets [19]. It has been suggested that changes in complexity in movement dimensionality can reflect subtle physiological change as it manifests over time [21]. This has been used in several studies to relate coordination patterns with changes in neurological state and motor capability [21–26].

Correlation structure features are represented by the eigenspectra of channel-delay correlation matrices as defined in a previous study [19]. "Channel" refers to the three acceleration axes, and "delay" refers to the time delays at which correlations are computed both between and within acceleration axes. Correlation matrices are constructed at four time delay scales, $\{d_1, d_2, d_3, d_4\}$, which have seven time delays per scale with delay spacings of $\{15, 35, 75, 155\}$, respectively. These delay spacings correspond to time delays of $\{0.03, 0.07, 0.15, 0.30\}$ seconds per scale. Another way to think of the matrix construction is that correlation matrices are constructed from an expanded number of acceleration time series, with the expanded number obtained via time-delay embedding of the original signals at multiple delay scales [19].

Specifically, a channel-delay correlation matrix at delay scale j is computed as

$$\mathbf{R_j} = \begin{bmatrix} R_{1,1}(j) & \dots & R_{1,M}(j) \\ \vdots & \ddots & \vdots \\ R_{M,1}(j) & \dots & R_{M,M}(j) \end{bmatrix} \quad (1)$$

where $M = 3$ is the number of low-level feature channels. Each submatrix $R_{c_1,c_2}(j)$ contains the set of correlations between channels c_1 and c_2 at scale j,

$$R_{c_1,c_2}(j) = \begin{bmatrix} r_{1,1}(j) & \dots & r_{1,N}(j) \\ \vdots & \ddots & \vdots \\ r_{N,1}(j) & \dots & r_{N,N}(j) \end{bmatrix}_{c_1,c_2} \quad (2)$$

where $N = 7$ is the number of delays per channel and $[r_{d_1,d_2}(j)]_{c_1,c_2}$ is the correlation, at scale j, between channel c_1 at delay d_1 with channel c_2 at delay d_2. The eigenvalues of the correlation matrix, R_j, rank ordered from largest to smallest, quantify the correlation structure and represent features for a given scale.

F. Modeling Feature Trends over Time

A linear model is used to compute the slope and intercept of each eigenvalue feature as a function of elapsed time. Correlations are then computed across subjects and sessions between the eigenspectra feature slopes and blast exposure levels. These correlations quantify eigenvalue feature change as a metric to distinguish among subjects with varying degrees of blast exposure.

Specifically, the linear trends of the eigenvalue features are estimated as follows. First, trends are only computed if there is a sufficient number of 5 s frames across a sufficient time duration for the resulting trends to be reliable. For Gait features, a minimum of 10 frames is required across a time duration of at least 30 minutes. Because LM frames are much more ubiquitous, a more stringent requirement is used for LM features of having at least 100 frames across a time duration of at least 30 minutes.

Next, the features from each session are z-scored, so that the trend is computed in standard units. Next, a linear function is fit to the normalized eigenvalues to capture the slope of the feature as a function of time. Because there are 105 eigenvalue features (3 accelerometry axes, 4 delay scales and 7 delays per scale), there are 105 gait and 105 LM feature slopes per session.

G. Predicting Blast Exposure from Feature Trends

The ability to predict blast exposure level from feature trends is evaluated using cross-validation training and testing of a regression model. Ten-fold stratified cross-validation is done, with a selection of subjects in each test fold designed to minimize variability in average blast exposure levels across test folds. In addition, multiple sessions from the same subject are assigned exclusively either to a training or a testing fold.

For each session, The 105 feature slopes across the four delay scales are concatenated to produce a single feature vector characterizing feature change. Next, in each cross-validation fold 10 principal components (PCs) are extracted across all subjects in the training set, and the PCA transform is applied to the test data. These PCs are used as input into the regression model described below. The 10 PCs explain on average 97.5% of the variance of feature slopes in the training data.

The regression model uses Gaussian mixture models (GMMs) that are trained on a staircase of class partitions between "low" and "high" blast exposure thresholds. There are 10 staircase partitions, based on thresholds of 100, 101, ..., 109 for dividing blast exposure levels between the low and high class. The likelihoods of GMMs trained to classify either the low or high class based on these ten partitions are summed together. The log-likelihood ratio computed based on these summed likelihoods produces a test statistics, which is then mapped into a blast exposure prediction using univariate 2nd order regression. This univariate regression model is constructed based on the test statistics in the training data. The staircase approach to regression is described in [23]. The approach in this paper differs from [23] by using GMMs instead of Gaussian models in each staircase partition.

The GMMs are trained using an unsupervised and supervised learning phase. Unsupervised training involves creating a universal background model (UBM) based on training data from both classes, in which Gaussian components are centered on randomly selected training data points, and then trained using L iterations of the expectation-maximization algorithm, which adjusts the means, diagonal covariances, and component weights. Supervised training involves, for each class model, adapting only the means of the GMM components toward the class data in the training set [27]. In addition, an ensemble of 5 GMMs is created per partition (with likelihoods summed across ensemble GMMs) to provide greater reliability with respect to the random UBM initializations. Table I describes the GMM parameters.

TABLE I
PARAMETERS GOVERNING GAUSSIAN MIXTURE MODELS (GMMS) TRAINED IN STAIRCASE DATA PARTITIONS.

Parameter	Value	Description
K	10	Number of GMM components
L	3	Number of batch learning iterations
σ_1^2	100	GMM initial variance
σ_2^2	1	GMM minimum variance
r	16	GMM adaptation parameter

III. RESULTS

The focus of the study is on characterizing the physiological effects of overpressure exposure. The focus of the present analyses are on detecting movement-related (i.e., gait and balance) changes across the period of exposure and relating the magnitude of change to the cumulative level of exposure. First, we report on the correlation of movement features and blast exposure. Next, we predict blast exposure from movement features alone, using a cross-validation train-test scheme.

A. Movement Features Across Periods of Exposure

The cumulative exposures, reported as an 8-hour equivalent of the A-weighted impulse noise level (L_{Aeq8hr}), ranged from 97 dB SPL to 118 dB SPL. The majority of exposures were in the range of 102 dB SPL to 110 dB SPL. These levels of exposure are typical for breaching activities.

Acceleration data was analyzed from 44 data sessions from which there were associated blast exposure estimates. Based on the feature and session selection criteria in Sections II-D and II-F, a reduced number of Gait and LM sessions were analyzed in associating feature trends with exposure levels. For Gait features, there were 33 sessions analyzed, from 20 unique subjects, comprising a total of 2,335 frames. For LM features, there were 41 sessions analyzed, from 22 unique subjects, comprising a total of 14,262 frames.

Shown in Figure 1 is a representative example for a single session of data. The overpressure exposure data has two components. First is the 100 ms time-averaged A-weighted energy, represented in blue. Second is the peak impulses (red asterisks) that denote single events of particularly high (>135 dB) overpressure, typically corresponding to blast events. The cumulative exposure for this session was 101.94 dB SPL. On-body accelerometry data (Figure 1B) was recorded for the duration of the exposure periods. An epoch of gait data is illustrated. Focusing on the gait epochs in this example, normalized magnitudes of two eigenvalue features are shown in Figure 1C. These are the rank 1 (blue) and rank 8 (red) eigenvalues from the forth delay scale. To summarize the changes in the eigenvalue features across the period of blast exposure, a slope is computed for each eigenvalue feature. In this example, only two eigenvalue features are shown for visual clarity, but in full, there are 21 eigenvalue features per time-embedded scale, yielding 105 total features (see Section II-E).

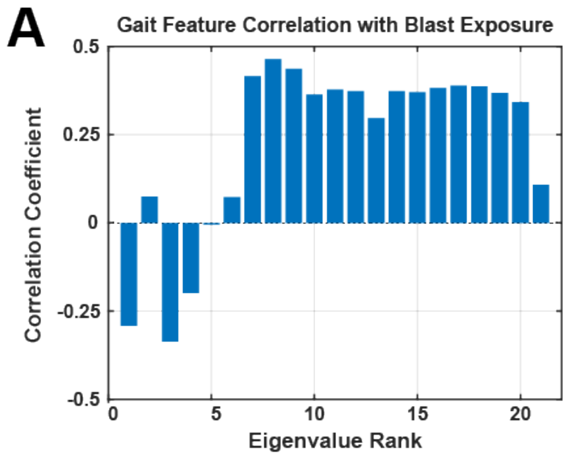

Fig. 3. Correlations between changes in eigenvalue features across an exposure period with the cumulative level of overpressure exposure. A) For the rank 1 and rank 8 correlations, the full set of data are shown in Fig. 2. By extension, the bar graph shows the correlations for the other eigenvalue features that were computed during periods of gait. B) Correlations between eigenvalue features, computed during low movement (LM) periods, and the level of overpressure exposure is shown.

B. Correlating Movement Features with Overpressure Levels

For each session of data, the slope of the eigenvalue features was computed. Building on the example shown in Figure 1C, the data for all subjects are shown in Figure 2. Here again, the slopes from only two eigenvalue ranks are shown for simplified visualization. The example session shown in Figure 1C is highlighted in red. For the rank 1 eigenvalue in Figure 2A, there is a negative trend in feature slopes as a function of level of exposure. However, for the rank 8 eigenvalue (Figure 2B), the opposite is true and there is a positive trend in feature slope with respect to level of exposure.

The relationships between eigenvalue feature slopes across subject and the level of exposure, exemplified in Figure 2 for two eigenvalues, is shown in Figure 3. The low-rank eigenvalues, which explain more of the variance in the data, putatively represent gross movement, whereas the higher rank eigenvalues, explaining less variance in the data, potentially represent more subtle movements either in gait or in relatively-stationary periods. The Spearman correlations between eigenvalue features and blast exposure, computed during gait periods, are shown in Figure 3A, while those relationships, for features computed during LM periods, are shown in Figure 3B.

The first notable difference between the two sets of features is that they have an opposite pattern of correlations across eigenvalue ranks. For gait, the time trend (i.e., the slope) of higher rank eigenvalues is positively correlated with the level of blast exposure. For LM, on the other hand, the time trend of higher rank eigenvalues is negatively correlated with the level of blast exposure. The second difference is that the magnitudes of these correlation are higher for the gait features as compared to the LM features. This is true both for the low and high rank eigenvalues.

C. Predicting Exposure Levels from Accelerometry

For both Gait and LM features, the 10-fold cross-validation regression procedure described in Section II-G was used to predict blast exposure levels. LM features did not produce predictions with statistically significant accuracy, so the predictions based on Gait features are illustrated.

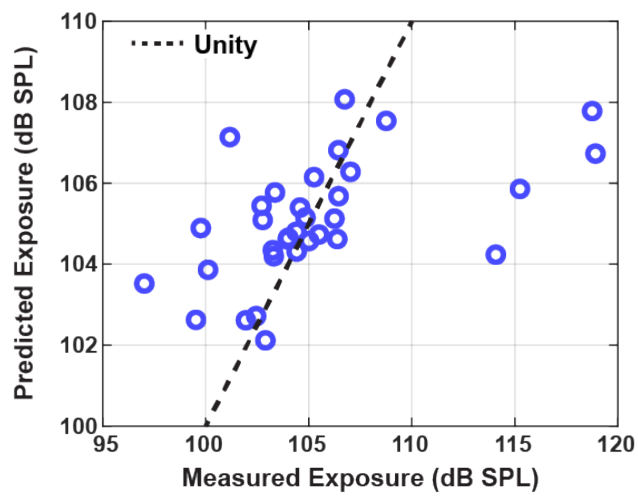

Fig. 4. Prediction of blast exposures from gait features. The dimensionality of the features are reduced using PCA and 10 PCs (97.5% of the variance) are retained. Model was trained using 10-fold cross-validation and accuracy is reported on held-out data. The slope of the fit is statistically significant ($p = 0.0013$). The RMSE = 1.27 dB.

Figure 4 plots the prediction results across all 10 test folds. The red line shows a linear fit to the predictions. Correlations of predictions with truth are Pearson $r = 0.51$, ($p = 0.0013$) and Spearman $r = 0.61$, ($p = 0.0002$). The prediction error, in the form of root mean squared error, is RMSE = 1.27 dB. $R^2 = 0.31$ indicating about 30% of the variance in the data is explained by the model.

D. Influence of Duration of Physical Activity

The activities involved with breaching training can be physically demanding. The average duration of a session was 5.1 $\pm$ 1.7 hours. As such, there may be an influence of fatigue on the changes in physiology that co-vary with the exposure to overpressures. To test this possibility, we computed the within-subject correlations of features with time duration. Here, duration is taken as a proxy for fatigue level, where longer durations of activity would indicate higher levels of fatigue. For both Gait and LM features, within-subject feature-time correlations were small and statistically insignificant. Across all four delay scales and eigenvalue ranks (105 features), the median Gait correlations were between -0.15 and 0.15, while the median LM correlations were between -0.1 and 0.1 (cf. Fig. 3). While the influence of fatigue cannot be ruled out, it is unlikely that duration was a significant covariate in explaining the relationships between feature trends and blast exposure levels.

IV. Discussion

We performed continuous overpressure dosimetry paired with on-body accelerometry for the duration of exposure. From the accelerometry data, we detected changes in gait and low-movement features. The changes across the period of exposure were correlated with the level of overpressure exposure. Our model, trained using 10-fold cross validation, was able to estimate the cumulative level of overpressure exposure from gait signals alone.

A. Changes in Body Movement After Overpressure Exposure

The key finding is that there is information contained in the body-worn accelerometry signals that can indicate exposure to blast overpressures. Of specific interest is the accumulated effect of repetitive exposures to high-energy overpressure waves (i.e., $>$135 dB). There are a number of studies in animal models that have shown the acute effects of repetitive blast overpressure exposure (e.g., [28]). Yet, translating the results to humans has proven challenging either because the ability to collect data in operational environments is limited to pre/post assessments, or the acute effects are variable, subtle, and typically sub-clinical. To overcome these challenges, we have focused on collected on-body accelerometry for the duration of the overpressure exposure. The magnitude of data quantity in the present study, stemming from continuous, non-intrusive monitoring, enables more sensitive assessment of subtle neurophysiological changes. Further, the simultanous accelerometry and overpressure dosimetry links the specific changes of the individual with the level of overpressure they experienced.

B. Gait vs Low-Movement Features

The analytical framework focused on gait and LM features. However, the gait features proved to be better correlated with the levels of blast exposure than the LM features and further, showed significant capability at predicting the levels of exposure in the cross-validated scheme. Taken together, there appeared to be a greater effect on the gait of the participants as compared to their LM (i.e., sitting or standing still) activity. In prior work, wherein gait and standing body sway (i.e., LM) were assessed on individuals with mild traumatic brain injury, gait features again proved to be more informative at detecting sub-clinical deficits [12]. Dynamic movements, or actions requiring multisensory integration, may help to elucidate the subtle effects of blast exposure [29].

C. Interpretation of Changes in Eigenvalue Features

The eigenvalues features, prevalent in the presented analyses, are inherently sorted in terms of the amount of variance they explain in the data. Low rank eigenvalues explain more of the variance and the higher the rank, the less variance explained. Yet, it appears that the higher rank eigenvalues (e.g., ranks 5 - 10) are better correlated with overpressure exposure. This points to the fact that more subtle changes in movement are being impacted by overpressure exposure, which makes the overt clinical detection challenging. Prior works by Williamson et al. [21–23] have shown that the eigenvalue features, as utilized here, provide insight into changes in motor coordination, that in turn can be used to assess neurophysiological status.

D. Limitations & Future Work

The present analyses have focused on a single sensing modality – on-body accelerometry. Though a crucial step in showing that there is information in the signals that can be used to assess overpressure exposure, the strength of the predictive models could be improved by combining additional relevant sensing modalities, like eye movements [30], that are simultaneously and continuously collected. The model explained about 30% of the variance in the overpressure exposure data. Improvements could be made by assessing the many other aspects of the blast exposure signals (e.g., impulse, duration) [31]. Further, there may be other relevant variables that we have not captured (e.g., angle of the head relative to the blast, recovery time between exposures, individual medical history) that could contribute to the neurophysiological changes. More in-depth data collections are needed to build models that may then explain more variance in the data.

V. Conclusion

We measured overpressure dosimetry, simultaneously with continuous on-body accelerometry, as military and law enforcement breachers performed training activities. Gait and Low-Movement (LM) frames were extracted from the accelerometry signals and eigenvalue-based features were computed on both sets of frames. The changes in gait features across the period of blast exposure were better correlated with the cumulative levels of exposure, as compared to the LM features. A model using gait features alone was able to significantly predict the individual's cumulative level of blast overpressure exposure.

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