Burnout: A Wearable System for Unobtrusive Skeletal Muscle Fatigue Estimation.

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***Abstract*—Skeletal muscles are pivotal for sports and exercise. However, overexertion of skeletal muscles causes muscle fatigue which can lead to injury. Consequently, understanding skeletal muscle fatigue is important for injury prevention. Current ways to estimate exhaustion revolve around self-estimation or inference from such sensors as force sensors, electromyography e.t.c. These methods are not always reliable, especially during isotonic exercises. Toward this end, we present Burnout - a wearable system for quantifying skeletal muscle fatigue in an exercise setting. Burnout uses accelerometers to sense skeletal muscle vibrations. From these vibrations, Burnout obtains a region based feature (R-Feature), in the case of this work, the region mean power frequency (R-MPF) gradient to correlate the sensed vibrations to a known ground truth measure of skeletal muscle fatigue, i.e., Dimitrov's spectral fatigue index gradient. We evaluate Burnout on the biceps and quadriceps of 5 healthy participants through four different exercises, collected in a real world environment. Our results show that by using this R-MPF feature on our real world data set, Burnout is able to reduce the error of estimating the ground truth fatigue index gradient by upto 50% on average compared to using the standard MPF feature.**

I. Introduction

Muscle fatigue is the progressive decline in muscle performance, strength and power during a particular exercise [4], [5], [33]. In excess however, muscle fatigue can result in injury due to muscle overuse, unnatural joint motions and abnormal joint stresses. These injuries have been observed in particular in young athletes at all levels and can lead to lifelong pain and handicaps if left unchecked [11], [16], [30]. Quantifying the level of fatigue in a muscle and providing this information to athletes, would allow the athletes to pace themselves adequately during an exercise. This, in turn would help them to take precautionary action against over exerting or injuring themselves.

Currently, most athletes quantify the level of fatigue during a workout based on their own self assessment or assessment from a buddy or coach. Self reported measures of fatigue e.g., Borg scales tend to be subjective, have low sensitivity and be inaccurate as one could underestimate their level of fatigue and get injured [18], [32]. While more accurate, experienced coaches are not always available to help monitor fatigue. Gym buddies, on the other hand, may not always be trained to know when a fellow exerciser is exerting themselves beyond a level of fatigue that they can cope with.

Recently, some have used sensor-based fatigue inference approaches e.g., electromyography (EMG) or mechanomyography (MMG)to infer muscle fatigue [12], [14], [18], [19]. However, most of these works have focused largely on determining fatigue in isometric exercise as opposed to more dynamic exercises e.g., isotonic periodic exercises [19], [22]. This is because in isometric exercises there is no motion noise and the muscle length remains constant while the muscle is tensed (contracted) making sensing and inferring muscle fatigue easier [10], [12]. Isotonic periodic exercises however, involve changing joint angles and usually contain a concentric and eccentric motion phase.

During the concentric phase, the muscles are worked under contraction, i.e., the length of the muscle decreases. The opposite happens during the eccentric phase, the muscle length increases while the muscle is being worked [12]. Muscle fatigue inference from features such as Mean Power Frequency (MPF) becomes difficult due to the change in muscle fiber length, coupled with body the motion noise induced in the sensed data due to changing joint angles [10], [12], [19], [22].

Toward this end, we present a wearable system called Burnout, for sensing, and estimating skeletal muscle fatigue. Our system relies on a network of wearable sensor nodes to detect mechanical muscle vibrations that occur during regular exercise when a muscle is activated. Burnout can quantify skeletal muscle fatigue during isometric exercises (static no motion exercise) as well as during isotonic exercises (dynamic controlled periodic motion exercise).

Since dynamic motion introduces noise that affects the features used for muscle fatigue estimation, Burnout's feature extraction process varies depending on whether exercise is isometric or isotonic. Specifically, in the case of an isotonic periodic exercise, Burnout extracts region based features (R-features). R-features are calculated using muscle vibration data that are roughly from the concentric phase of the isotonic exercise. We select the concentric phase of an exercise because this is the phase of an isotonic exercise where the muscle is being worked under contraction like in an isometric exercise, where a number of features have been shown to correlate with fatigue [10], [12], [19], [22]

Based on this concept, we introduce R-MPF, the region based mean power frequency feature. Using this R-MPF feature our system builds a regression tree model that it uses to estimate the gradient of the Dimitrov spectral index of fatigue, a widely used estimate of muscle fatigue [12], [17].

The contributions of this work are threefold:

1) We design and build a wearable, multiple-role multiple sensor, muscle fatigue sensing system that is unobtrusive, scalable and conducive for in-the-field exercise use.
2) We demonstrate how to quantify skeletal muscle fatigue using intuitive region based features (R-features) from the concentric part of an exercise that outperform the

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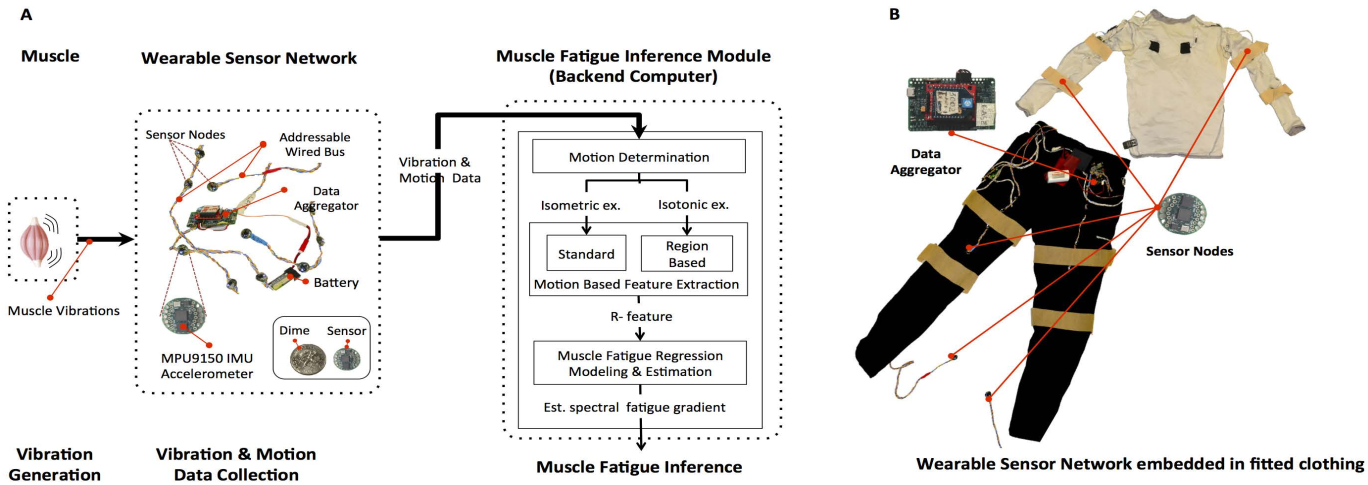

Fig. 1. Figure A shows an overview of the three components that make up the Burnout system. First, active muscles produce muscle vibrations. Second, the vibrations are sensed by the sensor network. Each sensor node has an accelerometer that can sense muscle vibrations as well as provide a coarse estimate of body motion. In set, the size of an American dime is shown for comparison, beside one of our sensor nodes. The data aggregator coordinates the sensing and data storage/ transmission to the backend computer. Finally, the backend computer, via the muscle fatigue inference module, processes the signal to estimate muscle fatigue. Figure B shows the wearable system with the wired sensor network embedded in fitted spandex clothing.

non region based versions.

3) We provide a modified windowing scheme for extracting the R-features that allows the feature extraction procedure to be robust to the periodic imperfections of a true isotonic exercise environment.

To show the efficacy of our method, we evaluate Burnout on the biceps and quadriceps of five healthy participants through four different exercises, collected in a real world environment. Our results show that by using this R-MPF feature on our real world data set, Burnout is able to reduce the error of estimating the ground truth fatigue index by as much as 50% compared to the standard MPF feature.

The rest of the paper is organised as follows. *Section II* provides an overview of the Burnout system. In *section III* we describe Burnout's system architecture in depth. The experimentation and data collection procedures are provided in *section IV*. *Section V* presents our system evaluation results. In *section VI* we mention some of the practical aspects and implications of our work. Next we discuss related work in *section VII* and finally conclude in *section VIII*.

II. System Overview

Burnout estimates muscle fatigue by sensing and processing the muscle vibrations produced by active muscles. To do this Burnout relies on a wearable sensor network for collecting the muscle vibration and motion estimation data necessary for muscle fatigue estimation in both isometric and isotonic exercise environments. The sensor data are processed by a muscle fatigue inference module located on a backend computing device. Figure 1-A shows these components of the system. Figure 1-B shows what the wearable version looks like with the sensor network embedded in fitted clothing that a human can wear.

A. Physiology of Skeletal Muscle

Skeletal muscles consist of muscle fibers which contract and relax to enable movement in response to electrical impulses from the central nervous system [5], [31], [37]. During this contraction process, the muscle fibers slide against each other and encounter friction, producing low amplitude skeletal muscle vibrations whose constituent frequencies vary between 5 to 100 Hz [5], [31], [37]. As a muscle fatigues, the firing rate of the muscle reduces due to a decline in the number of motor units available for activation [19]. Lower firing rates means slower movement of muscle fibers. This results in a shift of the frequencies in the sensed muscle vibration toward lower frequencies [17], [31], [37]. This is the physiological principle Burnout uses to estimate muscle fatigue.

B. Wearable Sensor Network:

To capture muscle vibration and motion estimation data we use a wearable sensor network.

The sensor nodes that make up the sensor network are small, light weight and contain triple axis accelerometers. Using these accelerometers the sensor nodes simultaneously perform two synergistic roles.

1) **Muscle vibration sensing:** Since the sensor nodes are small and light weight, they couple easily with low amplitude disturbances, allowing them to sense the low amplitude muscle vibrations required for muscle fatigue estimation.
2) **Motion estimation** The accelerometers contained in the sensor nodes also coarsely detect body movement. This allows Burnout to determine isometric from isotonic exercises and eventually extract the R-features described in section III-C.

The data collected is sent to a data aggregator node and transmitted to a backend computer for muscle fatigue inference. We describe the wearable sensor network in detail in section III-A.

C. Motion Determination

Motion Determination is the first processing step undertaken by the Muscle Fatigue Inference module that resides on a backend computing device. It is a threshold-based process of determining whether the average amplitude and periodicity of a **motion estimation sensor's** data are from an isometric or isotonic exercise. With this knowledge Burnout extracts features accordingly. We provide more details in section III-B

D. Motion Based Feature Extraction

Our motion based feature extraction is the process of extracting features depending on the type of exercise (isometric or isotonic), as determined by the motion determination phase. In the case of an isometric exercise, standard feature extraction is used. That is, it involves extracting the feature from all the windows of data in the entire exercise. However, in the case of a isotonic exercise, **region based** feature extraction is used so as to obtain region features (R-features). We extract R-Features features from data that correspond to the concentric region of an isotonic exercise, using a modified windowing technique. Based on this technique, we extract the region based MPF (R-MPF) by combining the MPF features from windows of data aligned with concentric regions. We provide more details of our approach in section III-C.

E. Muscle Fatigue Regression Modeling & Estimation

Muscle fatigue regression is the process of using a regression tree model to learn the mapping of the R-MPF feature to a known ground truth index of muscle fatigue. We use the Dimitrov spectral index described in section III-D1. We use this metric because it provides us with a well established and robust index that correlates well with muscle fatigue in both isometric and isotonic exercises [12]. More details on the regression modeling approach are also provided in section III-D.

Once the model has been learned, Burnout uses it to estimate a new Dimitrov spectral index gradient, as a measure of fatigue. More details on this process are described in section V.

III. System Design

In this section we describe our Burnout system in detail.

A. Wearable Sensor Network

As we mentioned in section II, the wearable sensor network senses both muscle vibrations and coarsely estimates body motion. The wearable system consists of three main components: 1) sensor nodes, 2) an addressable wired bus and 3) a data aggregator node.

1) Sensor Nodes: Burnout contains a total of 10 lightweight sensor nodes. Each sensor contains an off-the-shelf (OTS) inertial measurement unit (IMU), the MPU 9150, that includes a triple axis accelerometer. Burnout uses the accelerometers on some of its sensor nodes to sense muscle vibration and the rest to coarsely estimate body motion as we shall demonstrate later section III-C.

In addition, sensor nodes also contain an Atmega 328 microprocessor that is responsible for ensuring that the accelerometers are sampled per the data aggregator's instructions, at a 500Hz sampling rate. To band-limit the accelerometer signal, we used the MPU9150s in-built 1st order 98 Hz anti-aliasing low pass filter.

For purposes of wear-ability, we coated the sensors in a light weight clear epoxy. This made the sensors sweat resistant, durable and comfortable to wear.

2) Addressable Wired Bus: The addressable wired bus is a software augmented SPI bus used for sensor node data transport within the entire sensor network. It is made up of braided wires that physically strengthen the entire sensor network, making it robust to pulling and tugging stresses associated with regular exercise.

3) Data Aggregator: The data aggregator contains among other components, a Atmel SAM3X8E ARM Cortex-M3 microprocessor, a micro SD card port and a wireless xbee module. The processor allows for efficient coordination of sensor node sampling, logging of sensor data to SD card as well as wireless data transmission via the xbee radio to the backend computer's muscle fatigue inference module.

Next, we describe the motion determination module in detail.

B. Motion Determination

As mentioned earlier, Burnout sensor nodes take up two simultaneous roles **muscle vibration sensing** and **motion estimation**. The motion determination module leverages the latter to facilitate the former.

During an isometric exercise, the level of body motion is minimal, meaning that features calculated using these vibration data have less noise. However, during isotonic exercises, body motion creates unwanted noise that makes using features calculated from isotonic exercise vibration data less than ideal for muscle fatigue determination [12], [27]. Consequently, knowing whether an exercise is isometric or isotonic helps Burnout to determine how to extract the MPF feature that it requires for muscle fatigue determination.

To determine if an exercise is isometric or not, Burnout leverages the fact that during isotonic exercises, adjacent limb segments have a larger range of motion than during isometric exercises. In addition this larger range of motion tends to be periodic in an isotonic exercise as opposed to an isometric exercise.

For example, during an isotonic leg extension exercise, shown in Figure 5-A1, which works the quadriceps, the shin of the active leg experiences a larger range of motion, which is periodic compared to the isometric leg extension shown in Figure 5-A2, where the shin is fixed in place. Therefore data from a **motion estimation sensor** located on the shin, will show a much higher amplitude during an isotonic exercise relative to an isometric exercise. Moreover the motion estimation sensor data will show periodicity as well, during the isotonic exercise.

To separate an isometric from an isotonic exercise we first low pass filter and detrend the motion estimation sensor data. Next, we set a configurable amplitude threshold, T_{mot} and a configurable periodicity threshold T_{period}, for the **motion estimation sensor** data. If the combined triple axis magnitude of the motion estimation acceleration is greater than T_{mot}, and its periodicity is defined and greater than T_{period}, we consider the exercise to be an isotonic exercise. Otherwise the exercise is considered isometric. T_{mot} and T_{period} can be adjusted depending on the desired application. In our case experiments

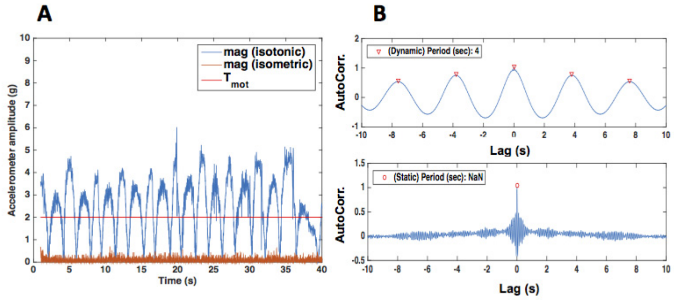

Fig. 2. Figure A shows how the magnitude of the scaled accelerometer data from a 'motion estimation' sensor compares in an isotonic leg extension exercise (higher amplitude) case vs. an isometric leg extension exercise (lower amplitude) case. A threshold of T_{mot} = 2g (horizontal line) can be used to separate the exercises. Figure B shows the auto-correlation with a lag of 10 seconds, for the isotonic leg extension **(top)** and isometric leg extension exercise (bottom).The **(top)** shows that the isotonic ex. has a periodicity of 4 seconds while the **(bottom)** shows that the isometric ex. is not periodic.

were performed using gentle controlled movements so that setting the T_{mot} = 2g and T_{period} = 2 seconds allows us to separate these two types of exercises.

Figure 2A shows sample motion estimation data from a sensor placed on the shin of a participant during an isotonic leg extension exercise and isometric leg extension exercise. Figure 2B shows the auto-correlation of the motion estimation sensor data during the isotonic exercise **(top)** and during an isometric exercise **(bottom)**. As we can see, isotonic exercises generate much higher signal amplitudes than the isometric exercises. In addition, the motion estimation sensor data shows a period of 4 seconds during the isotonic exercise but no period at all during the isometric exercise.

C. Motion Based Feature Extraction

Once the type of exercise has been determined in the motion determination stage, the next step is to calculate features from the vibration signal to use for fatigue estimation. We refer to the resultant feature as a region feature or **R-feature**.

If the exercise is determined to be isometric, then the R-feature that results from the feature extraction phase is simply the given feature calculated in a standard way. However, in the case of an isotonic exercise, the R-feature is extracted using a region based approach, i.e., from the region of data that corresponds to the concentric region /phase of the exercise.

As an example, our work focuses on the mean power frequency (MPF) feature, resulting in the calculation of our **regional mean power frequency (R-MPF)** feature. As we shall show in section V, the R-MPF gradient is a better feature for estimating the slope of the relative change in the Dimitrov spectral fatigue index, compared to the standard MPF feature gradient, particularly for isotonic exercise muscle fatigue estimation.

Next, we define how the MPF is calculated. Subsequently, we explain what the **Standard** and **Region Based** approaches are.

1) ***Mean Power Frequency (MPF):*** The mean power frequency (MPF) is the frequency value at which the average power of a signal is concentrated. It is calculated from 5 Hz high pass (HP) filtered accelerometer (MMG) data obtained

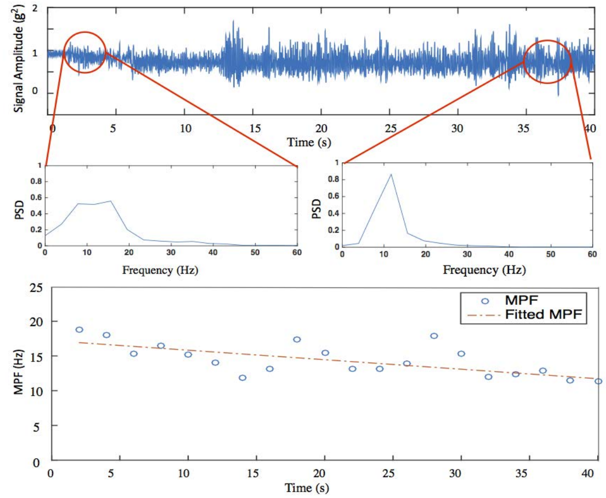

Fig. 3. **Top** graph in this figure shows sample MMG data from a fatiguing isometric bicep curl exercise. The signal amplitude is the summation of square of the individual accelerometer axes data. **Middle** graph shows the normalised power spectral density (PSD) calculated from a 2 second window of data (red circles) at the beginning (left) and then towards the end of the exercise(right). There seems to be a shift of signal power to lower frequencies evidenced by the change in shape of the PSD graph. There is also an increase in signal power as the muscle fatigues. **Bottom** graph shows a scatter plot of the MPF points and a fitted MPF line, extracted from consecutive 2 second windows through out the 40 second exercise. The gradient of the fit decreases further into the fatiguing exercise. This suggests a decreasing MPF trend with increasing biceps muscle fatigue.

from our sensors, placed on the muscle a interest. The calculation is as follows:

$$MPF = \frac{\int_{f1}^{f2} f.PSD(f).df}{\int_{f1}^{f2} PSD(f).df} \tag{1}$$

where *PSD(f)* is the HP filtered accelerometer (MMG) signal's frequency domain power spectral density calculated using a windowed short time fourier transmform (STFT) approach. $f1$ and $f2$ are the lowest and highest frequency in the MMG signal, demarcating the MMG signal bandwidth.

Next, we explain how we obtain the R-MPF feature.

2) ***Calculating the R-MPF:*** The first step Burnout undertakes when calculating the R-MPF, is to filter the muscle vibration sensor data using a 5Hz high pass (HP) filter. Choosing 5Hz, has been shown in previous work to reduce the effect of external body motion due to trembling or tremors that occur during an isometric exercise [27]. After HP filtering, the muscle vibration data are ready for Burnout's region-based MPF (R-MPF) extraction.

As we mentioned earlier in section II, depending on whether the exercise is isometric or isotonic, Burnout will calculate the R-MPF feature using either the standard or region based approach.

a) ***Standard Approach:*** This approach is used in the case of an isometric exercise. The resulting R-MPF is equal to the standard MPF feature, calculated from equation 1 using the entire exercise data. This is to say that there is only one region in the exercise.

Specifically, to obtain this feature, all the exercise data are windowed and standard Short Time Fourier Transform (STFT) techniques used to obtain a set of MPF values for each window of data for the entire exercise. We use a window size of about 2 seconds. We find that at our sampling rate of 500Hz, using larger window sizes does not significantly change the MPF values calculated for each window in our filtered vibration data. However, using smaller window sizes sometimes resulted in inconsistent power spectral density estimates due to a lack of sufficient data points in the window.

After the set of MPF instances has been extracted, Burnout uses robust linear fitting to fit a line to the MPF points and stores the gradient of the fitted line as the feature of interest [15], [20], [21]. The fitted line usually reveals a decreasing trend with increasing fatigue because of the shift in the power of muscle vibrations to lower frequencies [12], [17], [19], [22]. This shift can be seen by observing the power spectral density (PSD) of the muscle vibration data before and after fatigue sets in. Figure 3 demonstrates this using biceps muscle vibration data gathered from a participant during an isometric bicep curl exercise. We explore more about this exercise in section IV.

b) ***Region Based Approach:*** This approach is used in the case of isotonic periodic exercises to yield region based (R-features), in our case, the R-MPF from specific regions of the filtered muscle vibration data.

Burnout uses regions so as to capture the fact that there are concentric and eccentric phases in isotonic exercises and the MPF feature might behave differently depending on which phase of the exercise the muscle is in, as we explained in section II-D [12].

In our work, we focus on the **concentric** phase of the exercise because it is the phase during which the muscle works while contracting much like in the simple isometric case. *By considering this phase, Burnout is in essence trying to obtain the MPF in a way that closely as possible mimics the isometric case, where the MPF feature behaves well.*

To extract the muscle vibration data that corresponds roughly to the concentric phase of the isotonic exercise, Burnout turns to the smoothed, detrended Z-axis accelerometer data of the **motion estimation sensor**. We use Z-axis data, since we place the motion estimation sensor with the Z-axis perpendicular to the direction of motion of the motion estimation limb segment, e.g., the shin, in the case of a leg extension exercise or forearm for a bicep curl exercise. We secure the sensor to the limb as we will show in section IV-C, so that it does not move. This ensures that it can only move in the direction that the limb joint allows, in the case of the shin, in-line with the motion of the leg extension.

Since all the sensors in the sensor network are time synchronized through the common wired bus, samples of data from both the muscle sensor and the 'motion estimation' sensor represent two views of the same phase of a isotonic exercise. The muscle vibration data captures the state of the muscle while the accelerometer data from the 'motion estimation sensor' captures the general motion experienced.

What is key here is that the smoothed, detrended accelerometer signal pattern is different for the concentric phase as compared the eccentric phase. This is because the 'motion

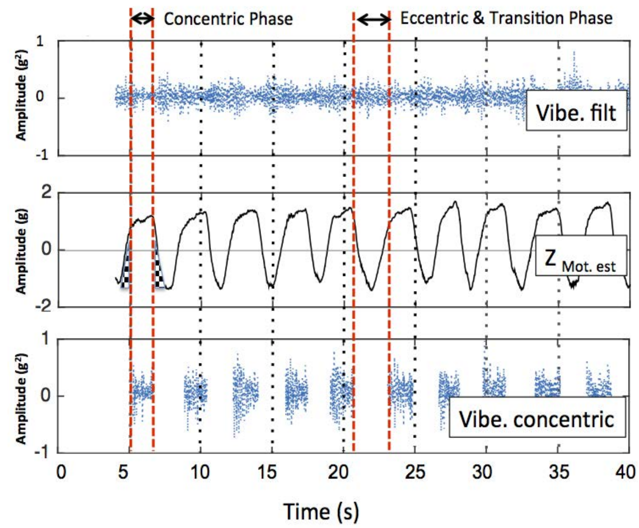

Fig. 4. A figure showing how we extract the concentric region muscle vibration data (Vibe. concentric) from the filtered muscle vibration data (Vibe. filt). The top graphs shows sample filtered muscle vibration data obtained from the quadriceps muscle during a isotonic leg extension. The middle graph shows the smoothed, detrended Z-axis data collected simultaneously from the *motion estimation sensor* ($Z_{Mot.est}$), placed on the shin of the exercising leg of the participant. The 'hill' areas of the ($Z_{Mot.est}$) demarcate the concentric parts of the exercise. The *checkered* areas show the 10% transition margin. The 'valleys' are the eccentric phase. The bottom graph shows how by using $Z_{Mot.est}$ on the Vibe. filt data, Burnout is able to select the concentric portion of the muscle vibration data (Vibe. concentric).

estimation sensor' is moving in opposing directions, up during the concentric phase and down during the eccentric phase. Therefore, obtaining concentric phase muscle vibration data is as simple as selecting the muscle vibration data that coincides with the 'motion estimation sensor' data when the estimator sensor data pattern closely matches the expected pattern of the concentric phase. Given our sensor placement, this region was the region where the smoothed, detrended Z-axis accelerometer data has a 'hill-like' shape as Figure 4 shows. However, since there is a transition from/to the eccentric part of before and after the concentric part of an exercise, we do not simply consider the entire 'hilly' portion of the data. Rather we consider only the muscle vibration data that is centered within the hilly portion, leaving a transition margin on each side. We empirically find that a 10% margin is sufficient to capture the concentric data that we need while excluding the unwanted transition parts.

Figure 4 shows this process. First, the HP filtered muscle vibration data *(Vibe. filt)*, as well as the corresponding Z-axis data of the motion estimation sensor, *(*$Z_{mot.EST}$*)*, are obtained and essentially overlaid on each other. Since during the concentric phase of an exercise, the exercising limb with the motion estimation sensor on it moved in way that revealed a 'hill' shape, only the *Vibe. filt* data that fall under the 'hilly' region, within the transition margins of the $Z_{mot.EST}$ data are selected, yielding the region based *Vibe. concentric* data.

After selecting the *Vibe. concentric* muscle vibration data Burnout marks the rest of the data for removal. This way when extracting the R-MPF feature, using a slightly modified windowed STFT technique, Burnout can exclude the 'marked' windowed data areas. We describe this modified technique next.

In order to correctly extract the R-MPF values from the remaining *Vibe. concentric* data, we have to align the windows from which R-MPF feature instances will be extracted correctly. This is because there are now 'missing values' in the *Vibe. concentric* data corresponding to the 'marked' non concentric areas. Therefore, windows of data must align with the concentric region areas to avoid the inclusion of motion distorted signals.

For this reason Burnout applies a modified windowing approach. Burnout subdivides all the exercise data into consecutive 'big windows', which may or may not align with the consecutive regions that we want. Next we subdivide the 'big windows' into n smaller windows. Now, we set a threshold $Thres_{ok}$, for percentage of small windows within a 'big window' that must be free of missing values. If the threshold is met, then the PSD of each of the missing value-free small windows is calculated, and averaged to obtain the PSD of the 'big window' from which an R-MPF feature instance will be obtained. If the threshold is not met, then the entire 'big window' of data is discarded.

Burnout uses this strategy so as to allow for the system to be tuned for different levels of misalignment *conservativeness*. For example, setting $Thres_{ok}$ too high, causes Burnout to be conservative so that only windows that coincide perfectly with the *Vibe. concentric* data are selected. This would however only happen if the period of the isotonic exercise matches exactly with the 'big window size' used for R-MPF extraction. However, in practice exercises are not performed perfectly periodically meaning that some misalignment error has to be allowed. If set too low, then all the 'big windows' of data are included, including unwanted areas, leading to distorted R-MPF feature instance calculations. Therefore, the configurable $Thres_{ok}$ parameter allows the windowing to be tuned according to application needs.

The value of n on the other hand determines the PSD resolution, hence the quality of the extracted R-MPF feature instance. If set too high, there is not enough data in a 'small window' to extract a meaningful PSD, leading to a poor overall PSD estimate of the 'big window' that detriorates the R-MPF feature. If set too low, then the configurability advantage of the misalignment error via $Thres_{ok}$ is lost, since there is only one small window, equivalent to the big window.

We find that using n=10 and $Thres_{ok} = 60\%$ yields acceptable results as we shall show in section V.

Once the R-MPF feature instances have been determined, Burnout uses robust linear fitting to fit a line to them [15], [20], [21]. Next, we extract the gradient of the fitted R-MPF line as the feature of interest.

D. Muscle Fatigue Regression Modeling & Estimation

After the feature extraction phase, Burnout has a set of R-MPF gradients.

The next step is to build a model for learning the relative change in the Dimitrov spectral fatigue index from our newly calculated R-MPF feature gradient values. This way Burnout can quantify muscle fatigue in terms of the relative change in the Dimitrov spectral fatigue index. This change has been shown to correlate with increasing muscle fatigue, particularly in EMG systems [12]. Next, we define what the Dimitrov spectral index is.

1) ***Dimitrov Spectral Fatigue Indices****:* In EMG systems, the Dimitrov spectral indices are the ratio between two varying spectral moments as shown in equation 2 [12]. f_1 and f_2 determine the bandwidth of the EMG signal and PSD represents the power spectral density of the EMG signal in a given window of the EMG data as a function of frequency f.

$$FI_{nsmk} = \frac{\int_{f_1}^{f_2} f^{-1}.PSD(f)df}{\int_{f_1}^{f_2} f^{k}.PSD(f)df} = \frac{M_{-1}}{M_k} \qquad (2)$$

Specifically we considered FI_{nsmk} constructed as the ratio between the signal spectral moment (M_k) of order (-1) and normalizing spectral moment of order k = 2,3,4 or 5. Spectral moments represent the area under the power spectral density curve after multiplication by the frequency raised to the power of k (order k of the moment) as the weighting function i.e.,

$$M_k = \int_{f_1}^{f_2} f^{k}.PSD(f)df \qquad (3)$$

The spectral moment of order k = -1 emphasizes the changes that occur in the EMG spectrum in the low and ultra-low frequencies. On the other hand, higher order spectral moments k=2 and above emphasize changes in the higher frequencies present in the EMG data [7], [14]. When the **relative change** in FI_{nsmk} is calculated for isometric and isotonic exercises, it shows an increasing trend, with increasing fatigue as shown in Figure 8 [7], [14]. Fitting a line to any of the relative change in FI_{nsmk} graphs, reveals a gradient that can be used to parametrize the increasing trend. It is this gradient that we are interested in estimating.

2) ***R-MPF to Dimirtov Index Modeling****:* To learn the mapping of the gradient of the R-MPF to the gradient of the relative change in the Dimitrov Fatigue index, we use a regression tree learning approach [9], [24].

A regression tree is a machine-learning method for constructing estimation models for variables that take continuous or ordered discrete values from data. The models are obtained by recursively partitioning the data space and fitting a simple estimation model within each partition, whose cost is measured by the squared difference between the estimator and estimated value. As a result, the partitioning can be represented as a decision tree [9], [24].

We chose to use a regression tree approach over linear regression approach because a regression tree approach tends to be more robust and less susceptible to factors such as non-linear data points or outliers that could throw off the learning process [34].

To train our model, we provide R-MPF gradients obtained from a muscle of interest as well as their expected label, i.e., the gradient of the relative change in the corresponding Dimitrov spectral fatigue index, value. The gradient of the R-MPF is therefore the estimator variable and the gradient of the relative change in the Dimitorv spectral fatigue index, the estimated value. We provide more details in section V-A.

With both the estimator and estimated values, the regression tree attempts to learn a piecewise linear model for mapping the R-MPF gradient values to the spectral fatigue index gradient values.

With a regression tree model learned, we can estimate spectral fatigue index gradient value from new R-MPF gradient instances and measure the error of the estimated spectral index gradient to the ground truth value. This error provides us with a system evaluation metric which we use to gauge how well Burnout works. We present these results in section V.

IV. Experimental Design

In this section, we describe the details of our experiments. Specifically, we elaborate on the human subject selection process, the sensor node placement details, and the exercise selection process for the real world system evaluation exercises.

A. Human Subject Selection

In order to evaluate our muscle activation system, we selected a group of five able bodied, healthy participants, aged between 18 and 45 years, to participate in our designated exercises. We selected this age group since most active athletes are of this age [36]. Three of the participants were male while the other two were female. All participants satisfied physiological health requirements set forth by a licensed physiotherapist so as to allow for a controlled experimental scenario, where unknown human factors were minimized.

Firstly, all participants were required to have no recent history of abdominal muscular or other injuries that would impede their ability to exercise. We focused on ensuring sound lower and upper extremity exercising ability since our experiments and exercises were designed around leg and arm exercises, which occur most frequently in sports and exercise. In addition, participants may not have been smokers or have blood pressure over 140/80. Participants also had to take part in some form of exercising activity e.g., gym going, running, soccer e.t.c so as to ensure that they were fit and had the muscle conditioning necessary to perform our selected exercises.

All the human subjects that we recruited for our experiments participated voluntarily. Moreover, in accordance with our institution, all experimental procedures were reviewed and approved by our institutional review board (IRB). Next we describe the exercises that we selected for evaluating Burnout.

B. Exercise Selection

The exercises that we evaluated Burnout on, worked the quadriceps and biceps muscles. The quadriceps exercises included a seated isotonic leg extension exercise as well as a seated isometric leg extension exercise. Similarly, to exercise the biceps, we selected a seated isotonic bicep curl exercise as well as a seated isometric bicep curl exercise.

Since our goal was to infer muscle fatigue, we took careful consideration when performing the selected exercises. For instance, each set of isometric or isotonic exercises was performed on different days, over the course of two months. A gap of at least two days of rest was enforced between two workout sessions. This ensured that they were fully rested before every exercise session and fully exhausted at failure.

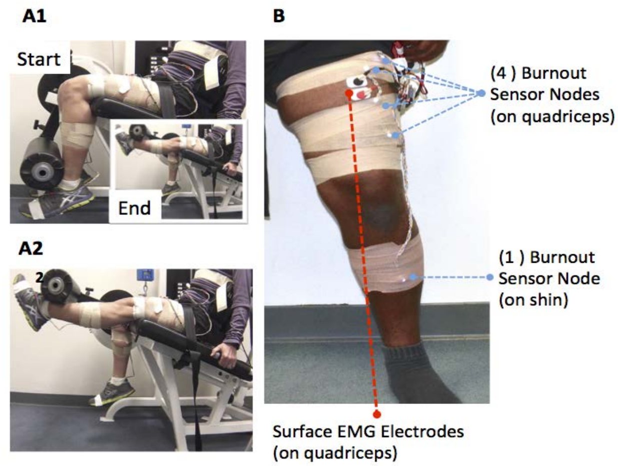

Fig. 5. A1 shows an isotonic leg extension from start to end (in-set), which works the quadriceps while involving motion. A2 shows an isometric leg extension exercise which involves statically working the quadriceps muscles. B shows how we placed Burnout sensors as well as surface EMG sensors on participants' quadriceps muscles in order to gather muscle data.

Moreover, all exercises were performed with a fixed exercise load equal to 40% of the Maximal Voluntary Contraction (MVC) weight. The MVC is the maximum amount of weight that an individual can lift. By assigning exercise resistance in this proportional way, the exertion level of the exercise was mutable, increasing or decreasing depending on the capability of the subject. We also found that using a higher exercise weight (>40% MVC), caused some participants to perform the exercise unreliably as they would shake and break exercise form unpredictably, risking injury.

1) Isotonic Leg Extension: We chose the isotonic leg extension so as to test if Burnout's modified MPF feature calculation algorithm would actually lead to a better MPF-Dimitrov spectral fatigue index mapping compared to the straightforward calculation approach used in previous work.

The seated isotonic leg extension exercise is shown in Figure 5-A1. During this isotonic exercise, the quadriceps are worked by smoothly and repetitively rotating the lower leg using the knee as a pivot while a weight placed on the leg provides exercise resistance. In our experiments, we used a metronome set at 30 beats per minute to pace participants when performing the exercise. This way we ensured that participants executed the exercise in a standardized manner. Since the aim of our experiments was to infer fatigue, participants performed the exercise until failure, the point at which they felt that that their muscles could no longer sustain the exercise.

2) Isometric Leg Extension: We selected the isometric exercise because so as to evaluate Burnout when used during an ideal exercise where the MPF feature works without modification.

The seated isometric exercise is shown in Figure 5-A2. In this exercise, the quadriceps muscles are worked without any movement. Instead, the participant simply holds their weight sustaining (exercising) leg in place to work the quadriceps muscle. Since no motion is involved in this exercise no

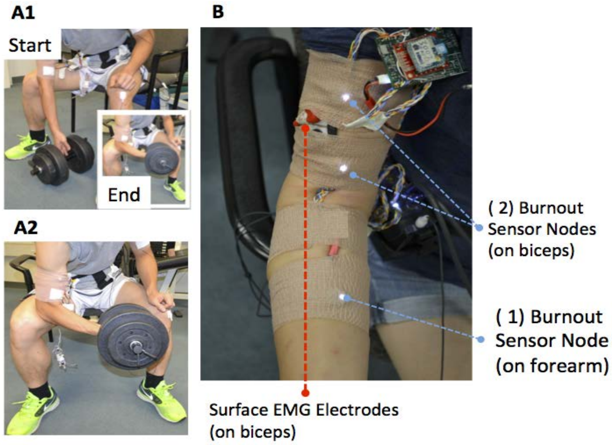

Fig. 6. A1 shows an isotonic bicep curl from start to end (in-set), which works the biceps muscles while involving motion. A2 shows an isometric bicep curl exercise which involves statically working the biceps muscles. B shows how we placed Burnout sensors as well as surface EMG sensors on participants' biceps muscles in order to gather muscle data.

metronome was necessary. As in the case of the isotonic leg extension, participants performed the exercise up to the point of failure.

3) Isotonic Bicep Curl: We chose the isotonic bicep curl because we wanted to evaluate Burnout on its ability to generalize fatigue to more than one muscle group.

The seated isotonic bicep curl exercise is shown in Figure 6-A1. During this isotonic exercise, the biceps are worked by smoothly and repetitively curling the forearm of the weight bearing arm towards the participant in a smooth, controlled motion, while using the elbow as a pivot point. To provide support for the curling arm, the participant braces the exercising arm's elbow with one of their knees as shown in Figure 6-A1.

Once again, this exercise, was performed at a speed of 30 beats per minute, under the guidance of a metronome to pace participants. Since the aim of our experiments was to infer fatigue, participants performed the exercise until failure.

4) Isometric Bicep Curl: The seated isometric bicep curl exercise is shown in Figure 6-A2. In this exercise, the biceps muscles are worked without any movement. Instead, the participant simply holds their weight bearing arm in roughly a right angle while bracing the exercising arm's elbow on one of their knees as shown in the figure. As before, participants perform the exercise up to the point of failure.

We selected the isometric exercise so as to evaluate Burnout when used during an ideal exercise but on a smaller and different muscle group.

C. Sensor Node Placement

In order to capture biceps and quadriceps muscle data, participants wore two types of sensors on either the biceps or quadriceps of the exercising limb. The first were the Burnout (accelerometer) sensors, which provided the muscle vibration data. The second set were surface EMG sensors from a industry standard surface EMG system, the NeXus-10 Mk I biofeedback system, from Mind Media Incorporated [26].

1) ***Burnout Sensor placement****:* Burnout sensor placement varied depending on the exercise being performed.

In the case of the quadriceps, subjects wore a set of five Burnout sensor nodes on the exercising leg's quadriceps muscle as shown in Figure 5-B. The sensors were held in place by woven elastic bands. Four Burnout sensors were worn on the quadriceps muscle of each leg. These sensors were centered in a lengthwise orientation along the quadriceps muscle. We use four sensors for redundancy reasons as well as to obtain sufficient data for future sensor placement studies. For the current work, we used data from the most centrally placed Burnout sense as it provided the strongest signal.

The remaining Burnout sensor was worn on the shin of the participant's exercising leg. This sensor was used as a motion reference sensor as described in section III-B to distinguish an isometric leg extension exercise from an isotonic leg extension exercise.

For the bicep curl exercise, participants wore three Burnout sensors as shown in Figure 6-B. Two of the Burnout sensors were secured on the biceps using woven cloth tape. We used vibration data from the top sensor since it was the sensor that was most centrally placed on the biceps muscle of the exercising arm.

a) Determining securing pressure for Burnout sensors: Since Burnout sensor nodes sense muscle vibrations on the skin, the quality of the sensed signal will vary greatly depending on how tightly secured the sensors are to the skin. For this reason, we selected the pressure used to secure our burn out sensors carefully.

If the sensors are not in contact with the skin at all, then no muscle vibrations or garbage data are sensed. If secured too tightly on the muscle using the cloth tape, then once again the sensed signal is weak and unsuitable for transmitting muscle vibrations to the sensor as Figure 7 shows.

We eventually found that the optimal pressure for securing Burnout sensors to the muscle was obtained when we wrapped the sensor around the exercising limb using one or two 'wrap-arounds' of woven elastic tape. We therefore held the Burnout sensor by going around it once or twice with the woven cloth tape when securing it to our participants muscles.

We used the 'wrap around' measure since it mimics how fitted clothing would be used to hold the sensors in a real world environment. Moreover, when placing the sensor nodes during our experiments, the number 'wrap-arounds' of woven elastic tape helped standardize our sensor placement in a practical way.

In this next section we describe our sensor node placement on participants quadriceps and biceps muscles.

2) ***Surface EMG Sensor placement****:* To obtain the sEMG based Dimitrov spectral fatigue index ground truth, we additionally instrumented each participant's muscles with sEMG electrodes. We placed a single electrode on either the quadriceps or biceps of the active limb of the participant as shown in Figure 5-B and Figure 6-B. The sEMG electrodes were placed as close as possible alongside the Burnout sensors so as to allow both systems to sense the same muscle.

Steps were taken to ensure the optimal performance for the sEMG system. The NeXus-10 MK I biofeedback system's electrodes were pre-gelled, meaning that no additional gel

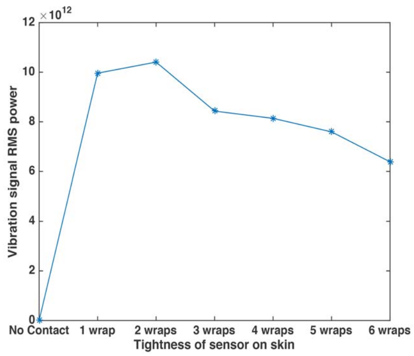

Fig. 7. A figure showing how the RMS power of the sensed muscle vibration signal varies with increasing binding pressure on the Burnout sensor nodes, during an isometric leg extension exercise. If the sensor is not secured at all (no contact) and there is no other movement, the RMS of the sensed muscle vibration signal is weakest. Once the sensor is secured on the muscle using one or two wrap-arounds of the woven elastic tape, the sensor begins to pick up on the muscle vibration signal which has much higher signal power. However, as the number of wrappings of the woven elastic tape increase, securing the sensor tighter and tighter on the body, the sensed muscle vibration signal power once again begins to decrease.

application was necessary. However, before application of the electrodes, a physiotherapist prepared the participants' skin according to the manufacturer instructions. Preparation steps involved shaving any hairs on the electrode application site as well as cleaning the application site with an alcohol prep pad.

The sampling rate of the sEMG machine was set to the maximum rate of 2048Hz. To mitigate noise due to body motion and other sEMG artifacts, all sEMG data was passed through a manufacturer recommended fourth order Butterworth 20Hz - 500Hz bandpass filter.

Next we evaluate how well Burnout was able to quantify muscle fatigue by predicting the ground truth surface EMG based Dimitrov spectral fatigue index.

V. Evaluation

In this section we present our system evaluation results that show how well Burnout was able to estimate the spectral fatigue index-based ground truth, using the gradient of the extracted R-MPF features.

In our experiments most participants lasted about one to two minutes. Given that a single R-MPF feature instance was obtained in each 2 second window, there were roughly 30-60 R-MPF feature instances being fitted to obtain an R-MPF gradient that parametrizes the fatigue for the entire exercise from start to failure. Therefore for each exercise, we estimated one spectral fatigue index gradient. We estimated the gradient because it is a measure of how quickly the muscle is fatiguing during that exercise.

Our evaluation metric was the error in the estimated gradient of the relative change in spectral fatigue index gradient compared to the true (ground truth) gradient value. We present this error in terms of its Cumulative Distribution Function (CDF). The CDF can roughly be interpreted as portraying the percentage of Spectral index estimations falling below a given error range.

We now briefly describe how the Spectral fatigue index was obtained from actual ground truth surface EMG data.

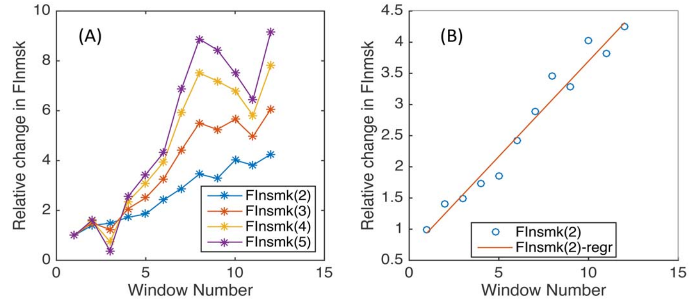

Fig. 8. Figure A shows the evolution of the relative changes in FI_{nsmk} for normalizing factors k = 2,3,4, against a window number (time), for data collected during an isotonic leg extension exercise from a test subject. Figure B shows how closely to a linear (regressed) trend (FInsmk-regr) the relative change in FI_{nsmk}, k=2, is, motivating it as our choice for ground truth. Similar trends were observed for isometric exercises as well.

A. Obtaining Ground Truth

In order to evaluate our system's ability to infer muscle fatigue we bench-marked it against a EMG-based measure as ground truth. EMG works in our case because the exercise durations are short ($<$ 3 minutes) and performed in a controlled manner. This way sweat and motion artifacts do not adversely affect the ground truth EMG signal. In addition, to mitigate the negative effect of motion artifacts, we had a licensed physiotherapist assist in identifying points of motion artifact pollution in the EMG data. These were manually removed to give a usable ground truth EMG signal.

The EMG-based ground truth measure that we selected was based on the Dimitrov spectral fatigue indices, FI_{nsmk}, described in section *III-D*. We selected this EMG feature as opposed to the MPF feature because when calculated from EMG data the Dimitrov spectral indices have better sensitivity for estimating muscle fatigue [12]. In addition, the Dimitrov spectral indices were ideal because they showed a similar trend for both isometric and isotonic periodic exercises. This meant that we could use a single exercise-agnostic ground truth measure of fatigue for a fair comparison regardless of the exercise being investigated.

As previously mentioned in section *III*, we calculated four FI_{nsmk}, with normalizing factor k = 2,3,4,5. A sample graph showing the evolution of the relative change in FI_{nsmk} for normalizing factor k = 2,3,4,5, during an isotonic leg extension exercise for one of our participants is shown in Figure 8A.

Upon visual inspection of the resultant features, we selected the FI_{nsmk} with k =2 to use as our EMG ground truth measure of fatigue. This choice was motivated by the fact that the FI_{nsmk} with k =2 showed the most monotonic linear like trend as shown in Figure 8B, allowing us to fit a line to its data, whose slope could be mapped to from the slope of the R-MPF feature that Burnout produces. This way, we could directly evaluate Burnout against the chosen ground truth.

B. Spectral Fatigue Index Estimation Results

To evaluate our muscle fatigue estimation system, we used the learned regression tree model described in section III-D, to estimate the gradient of the ground truth Dimitrov spectral fatigue index, of the quadriceps and biceps muscles.

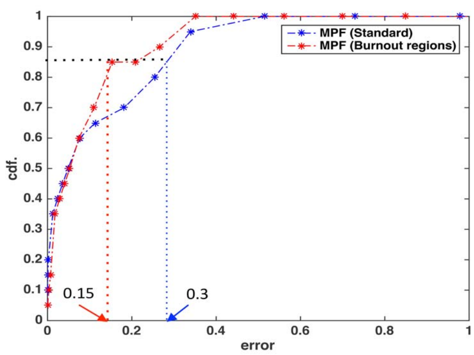

Fig. 9. A figure showing the CDF of the absolute error of estimating the ground truth. In blue we see the CDF of the error of estimating the spectral fatigue index gradient when the standard MPF feature gradient is used for estimation. The red line shows the CDF of the error using Burnout's R-MPF gradient. As we can see, for errors < 0.1 Burnout's method is almost equivalent to the standard MPF approach. However,when using Burnout, 85% of the extracted R-MPF gradient instances show estimation errors $<= 15\%$, whereas for the standard approach the same percentage of features show about 30% error on average. Therefore using Burnout's algorithm has halved the fatigue index gradient estimation error.

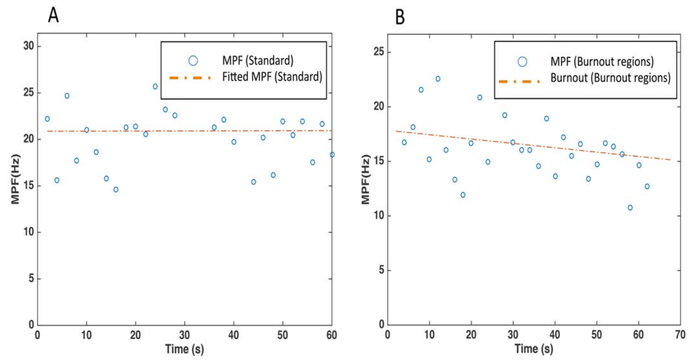

Fig. 10. Figure A shows the MPF feature calculated using the standard approach, from a participants quadriceps muscle vibration data. The data is from an isotonic leg extension exercise. The linear fit MPF for this case is also shown. Figure B shows what happens to the R-MPF feature calculated using Burnout's algorithm, i.e., using data from only the concentric phase of the isotonic leg extension exercise. As we can see, the MPF(standard) fails to show the expected decreasing trend with fatigue. Using Burnout's R-MPF, the trend is restored, even in the midst of isotonic exercise motion noise.

We achieved this using the standard leave one out cross validation (LOOCV) techniques. This is to say that we trained five different regression tree models for mapping R-MPF gradient values to spectral fatigue index gradient values. Each regression tree model was trained from all the R-MPF gradients obtained from all but one participant. Next we used the model to map the fifth participant's R-MPF gradient values to their spectral fatigue index gradient values. We then obtained the average of the estimation errors from all the runs as our evaluation metric.

We note that we obtained two sets of averaged error values. The first set of error values corresponds to those from Burnout, i.e., the error obtained when Burnout's exercise R-MPF feature gradient was used to estimate the spectral fatigue index gradient. The second set of errors correspond to those obtained when using a standard MPF feature gradient to estimate the spectral fatigue index gradient.

Figure 9 shows the cumulative distribution function of the average estimation error. The blue line *(MPF(standard))* shows the trend when using the standard MPF feature gradient to estimate the spectral fatigue index. The red line *(MPF(Burnout regions))* shows the error trend when Burnout's R-MPF feature gradient is used. As we can see, error values below 15%, are achieved from roughly the same percentage of estimations regardless of the method used. In other words, Burnout and the standard MPF technique are similar since the red and blue curves are almost identical.

However, as Figure 9 shows, when we consider the 85% of the estimations made using Burnout's R-MPF feature compared to 85% of the estimations made using the standard MPF technique, it is evident that Burnout clearly outperforms the standard approach. Using Burnout, the average error is less than 15% while it goes as high as 30% using the standard approach. Burnout essentially halves the estimation error. Moreover, Burnout continues to outperform the standard approach from this point onwards, reaching a maximum error of about 35%, against the standard approach's 55%.

This result can be explained as follows. The MPF feature gradient calculated using the standard approach is less noisy when obtained from a muscle being worked during an isometric exercise. However, during an isotonic exercise, changing muscle properties and body motion noise due to motion unsteadiness at the transition points where the exercise turns from an eccentric to a concentric phase, introduce noise into the muscle vibration data. This leads to the standard MPF feature being noisier than the R-MPF feature which is calculated only from the concentric part of the isotonic exercise, excluding all other phases of the exercise.

Figure 10-A shows an example of this. The MPF feature shown here was calculated using the standard technique from quadriceps muscle vibration data obtained from one of our experiments during an isotonic leg extension exercise. As we can see, we do not observe the expected negative gradient, as explained in section III-C2.

With Burnout however, the effect of the noise is mitigated by using R-MPF calculated from only the concentric phase of the exercise. This is possible because Burnout has multiple sensor nodes, some of which can be leveraged for motion estimation. Using motion estimation, allows Burnout to obtain more consistent concentric exercise phase MPF features, which lead to a better MPF gradient to spectral fatigue index gradient regression tree mapping. This results in lower estimation errors compared to the standard method. From Figure 10-B, we can see that the R-MPF feature extracted by Burnout does indeed show a declining trend as expected.

The regression tree model we created was 'global' in a sense. It did not depend on the type of exercise or muscle. The only restriction we placed was at an individual level. This is why we used an LOOCV training/testing approach to evaluate our system.

VI. Discussion

In this section we discuss some of the practical aspects of our work.

The primary focus of this work was to create and investigate the validity of using a new wearable MMG based system, Burnout, to quantify the level of fatigue in exercising skeletal muscles. In particular, we focused on extending muscle fatigue estimation, when using MMG, to isotonic exercises, from the isometric exercises that have been previously studied.

Focusing on isotonic exercises, allowed us to use the periodicity and concentric motions of the exercises to design selective R-features. In effect, these features filter out unwanted regions reducing the noise in our fatigue estimation features. Whereas, this method may be considered as being less general and more applicable to isotonic exercises, it is complimentary to some of our previous work in which we showed how to mitigate motion noise in more complicated exercises such as squats, cycling and jumping [27].

Our study also used strict fitness criteria mentioned to select of study participants. This meant that the participants were fairly homogeneous and did not have too much body fat. As a result we found that the gradients of the fitted R-MPF and Dimitrov spectral fatigue indices across the participants did not significantly vary and neither did the respective vertical axes intercepts. This made it possible for us to use a regression tree to map the gradients of R-MPF to map to the gradients of the Dimitrov spectral index.

In addition, having a homogeneous, fit population may have potentially reduced the negative sensing effect due factors such as the level of skin thickness, subcutaneous fat e.t.c. [23], [39], on our system. It is therefore possible that the Burnout system might have worked well given the test subject population and might fail or require further development if the participant pool were more diverse. Whereas this might be considered less than optimal, we argue that different versions of Burnout could potentially be trained that cater to participants of differing physical fitness.

VII. Related Work

In current literature, there exist works that investigate muscle fatigue and how muscle fatigue could be measured. We give a brief overview of these research efforts here.

One of the approaches used in studying muscle fatigue is electromyography (EMG) [4], [13], [25], [29]. Electromyography is a technique that involves using needle electrodes (fine-wire, EMG) or surface electrodes (surface electromyography or sEMG) to record the action potentials of working muscles. EMG is used to detect muscle fatigue because during a fatiguing muscle contraction, the reduction in the muscle conduction velocities (CV) and motor recruitment lead to a shift of the EMG power spectrum toward lower frequencies [12], [17]. This shift in frequencies is captured using features calculated from the EMG signal such as the, median frequency(MF), the mean power frequency (MPF), as well as the Dimitrov spectral fatigue indices [12], [17].

Most sEMG systems, while less invasive compared to the fine-wire alternative, tend to require careful placement of the electrodes, and expert handling of the system. This is because of sweat and motion artifacts which degrade the signal during use in active exercise scenarios [2], [4], [6]. By contrast, Burnout's system is waterproof, hence not affected by sweat, and can utilize its multiple accelerometer-equipped sensor nodes to estimate and mitigate the noise that pollutes the muscle vibration features used for muscle fatigue estimation.

In spite of the EMG challenges, we use EMG as a ground truth in our work when calculating the Dimitrov spectral index of fatigue gradient. This is possible because the exercises we perform contain well regulated motion over a short period of time, where sweat and motion artifacts do not adversely affect the signal.

While more traditional EMG techniques have the above limitations, there are other upcoming sEMG systems such as Athos Gear, that are designed to be used in sweaty, high movement exercise scenarios [1]. However, to the best of our knowledge, all the published demonstration material points to the use of Athos for determining muscle activation, muscle effort and not yet muscle fatigue.

Mechanomyography(MMG) on the other hand relies on externally sensing the mechanical vibrations produced by active muscles that were discussed in Section *II-A* using vibration transducers such as accelerometers [8], [27], [28], [37]. The challenge with MMG however, is that accelerometers measure body motion noise as well. This means that extracted features have to be carefully processed to reduce the effect of the body motion noise [27]. This has limited many prior works to using MMG in isometric exercises only [8], [37]. In contrast, Burnout directly addresses the motion problem.

Aside from the muscle sensing systems, researchers have used varying algorithmic techniques to determine muscle fatigue. Most of the current research in this area has focused on classifying non-fatigued vs. fatigued muscle, providing a low resolution or binary view of the fatigue status of a muscle [3], [4], [35], [38]. While these works have shown relatively high classification accuracies, it is the continuous onset of fatigue that is often times challenging to determine or sense and the time during which injury is imminent [4]. Consequently, with a more continuous/ high time resolution result about a muscle's fatigue status, exercising individuals might have sufficient data to pace themselves through an exercise, preventing injury.

VIII. Conclusion

In this work, we presented Burnout, a novel skeletal muscle fatigue estimation system. Burnout is a wearable system that relies on mechanomyography using accelerometers to sense muscle vibration and infer muscle fatigue. By leveraging its multi-sensor nature, Burnout is able to perform a simple yet effective motion estimation, which it leverages for region based feature (R-Feature) calculation. By using the gradient of an R-feature, such as the R-MPF, Burnout is able to learn a global regression tree model for quantifying the level of fatigue in a muscle in terms of the gradient of the Dimitrov spectral fatigue index. Burnout's estimation errors are about 50% less than those calculated using the standard MPF technique.

These results demonstrate the feasibility of using a system like Burnout to help quantify skeletal muscle fatigue in an exercise environment and possibly prevent injury from over exertion.

IX. Acknowledgments

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