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Electromyography as a surrogate for estimating metabolic energy expenditure during locomotion

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ABSTRACT

Minimizing metabolic energy expenditure (MEE) plays an important role in increasing mobility in people with locomotor disabilities, as movements that require high energy lead to less activity. Rehabilitation programs and devices use MEE to determine how effective they are, but using indirect calorimetry is limiting due to time delays and non-real-world conditions. Electromyography (EMG) offers insight into how muscles activate; thus, the purpose of this study was to develop a real-time MEE feedback system through the utilization of EMG signals. Participants completed five walking conditions at different stride frequencies (preferred, +/- 15%, +/- 30%), while breath-by-breath gas exchange, ground reaction forces and EMG signals were collected. The live EMG signal was numerically integrated and separated into strides, then scaled by a cost of force (COF) coefficient. MEE had the expected quadratic relationship seen in previous literature ($R^2 = 0.967$), along with COF data ($R^2 = 0.701$). The EMG method stabilized between 75.1% - 133.1%, which is not within a close range (90% - 110%) of MEE; thus, future studies must investigate other mathematical methods. Our results indicate a qualitative association between MEE and EMG activity, which could be used to increase mobility and quality of life for populations with disability.

1. Introduction

Minimizing energy expenditure during locomotion plays an important role in the animal kingdom, from small to large animals with differing forms of locomotion [1–3]. This principle applies to human movement across many walking parameters, such as stride frequency, step width, and gait speed to minimize energy costs [4–7]. People with disabilities may also minimize energy expenditure [8] but have mobility deficits that cause impaired locomotion, making it difficult to experimentally prove this with current methods. Development of assistive devices and rehabilitation programs use the measurement of energy expenditure to make an assessment of the macroscopic effects of the mechanism on the body [9,10]. If real-time metabolic data could be obtained during locomotion, it would give insight into how specific parameters could be adjusted to promote increased mobility and quicker recovery; however, this is difficult to achieve with current methods.

Currently, the most widely used approach to estimate metabolic energy expenditure (MEE) in engineering and biomechanics is indirect calorimetry (IC), which measures expired oxygen and carbon dioxide byproducts of the internal energetic demands to supply muscles and other organs with energy in the form of ATP. However, due to mitochondrial dynamics and oxygen exchanges that take place during circulation from the muscles to the lungs [11] a delay exists before oxygen usage presents itself in the respiratory gases [12,13], making it difficult to estimate direct metabolic energy expenditure in real-time. This leads to the fundamental limitation of indirect calorimetry, being the need to perform tests in which steady state levels are obtained over several minutes at a certain parameter to ensure that oxygen is being consumed at a sustainable rate [14], as well as high breath-by-breath noise present in the measurements [13]. The implications of these limitations make real-world comparisons difficult, wherein only one percent of walking lasts the required five minutes at steady parameters due to continually changing terrain or task objectives [15]. Changing terrain can require quicker and slower steps, with quicker steps having greater MEE than slower steps based on the cost of force relationship [16]. More importantly, people with disabilities are often unable to perform long bouts of

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steady state conditions due to mobility difficulties. The limitations of indirect calorimetry are well-acknowledged, resulting in the development of new methods to estimate energy expenditure.

An approach that is promising in estimating rapidly changing energy costs is measurement of muscle activity using electromyography (EMG), which records the myoelectric signals produced during muscle activation [16]. As the muscles perform a task, they are supplied with energy from both aerobic and anaerobic sources, implying that muscle activations correlate directly with dynamic energy expenditure [17]. EMG signals collecting muscle activation happening in real-time could significantly decrease the time delay in estimating MEE compared to IC (Fig. 1). Previous studies that examined EMG while walking were able to accurately predict metabolic energy expenditure validated side-by-side with indirect calorimetry, one under a specific set of ankle assisted walking conditions [18] and the other showing muscle activity minimized while walking at a preferred stride frequency (PSF) [19]. Additionally, results from another study were able to establish a relationship between metabolic power and EMG signals during non-steady state cycling conditions [17]. These studies indicate the potential for developing a robust method of determining energy expenditure from EMG signals. To the authors knowledge, there has not been a study to estimate real-time energy expenditure compared to indirect calorimetry while walking using EMG. If people with disabilities had access to immediate metabolic cost predictions for everyday movements, it could lead to quicker movement self-optimization and a better quality of life [20].

The purpose of this study was to develop a real-time metabolic energy expenditure feedback system using EMG. We hypothesized that real-time EMG would have the same qualitative (i.e., pattern) relationship as IC across preferred and non-preferred walking patterns. In addition to collecting unaltered muscle activity, we also were interested in incorporating scaling coefficients to investigate whether their inclusion would provide a better match to IC. We incorporated a coefficient approximating the cost of force required by each stride, which was calculated by taking the reciprocal of the time of each stride [21]. This was chosen to drive up MEE estimations for quicker stride conditions and lower MEE estimations for longer stride conditions and was hypothesized to provide a better match to IC. We hypothesized that the real-time EMG would have a different quantitative relationship to IC. We wanted insight into how quickly EMG could predict sudden changes in MEE, hoping the time delay that exists with indirect calorimetry can be decreased. Additionally, we wanted to know which muscle sets are the best predictors of MEE and hypothesized that larger muscles will have a greater contribution to energy expenditure and would be the best indicators of total energy costs.

2. Methods

Five healthy participants (age = 22.1 ± 1.1 yr., height = 1.7 ± 0.1 m, mass = 69.6 ± 14.3 kg, females = 3) took part in this study after giving informed written consent to protocols approved by East Carolina University's Institutional Review Board. The participants completed five different walking conditions at 1.3 $m \cdot s^{-1}$ on an instrumented treadmill (Bertec, Columbus, OH) at five-minute intervals after an initial five-minute static collection. The first condition was at the participant's PSF, and the remaining four were +/- 15% and 30% of the PSF in a random order. Each individual's PSF was recorded by making note of how many steps they took in one minute while walking during the first condition [22]. An audio metronome was used to indicate the desired frequency and the participant was directed to time each step to the beat. The participants walked continuously for the first three conditions, underwent a 60 second rest to prevent lagging in the program due to the amount of data, and then walked continuously for the final two conditions.

Breath-by-breath oxygen and carbon dioxide gas exchange were recorded (ParvoMedics TrueOne 2400, Sandy, UT) during the static and walking periods continuously. Additionally, ground reaction forces and

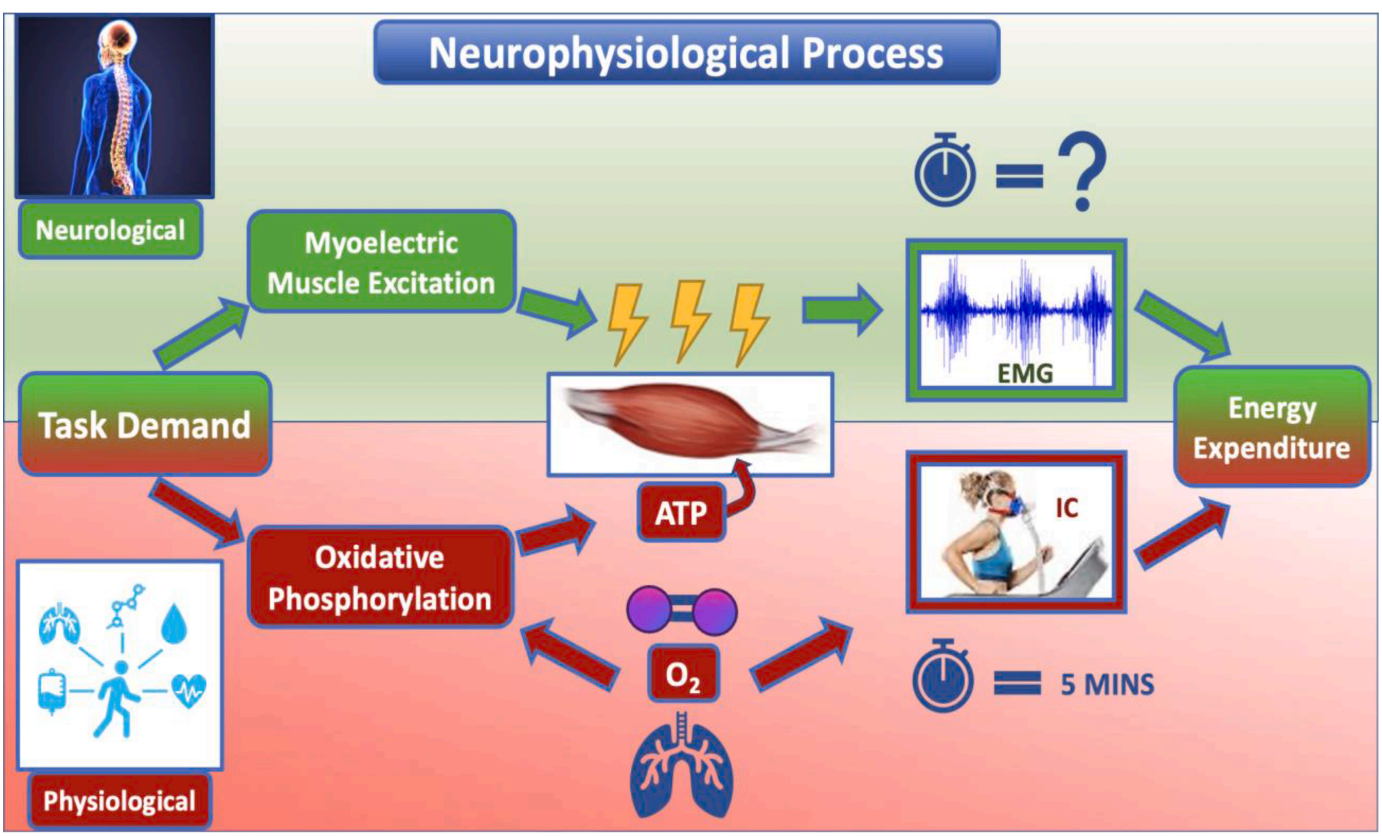

Fig. 1. Theoretical Framework Comparing Energy Expenditure Processes. EMG may significantly decrease time delay seen in IC giving reliable MEE estimates.

surface EMG (Motion Lab Systems, Baton Rouge, LA) signals were recorded throughout the trials. EMG sensors were placed on five muscles (biceps femoris (BF), rectus femoris (RF), vastus lateralis (VL), medial gastrocnemius (MG), soleus (Sol)) on each leg for all participants. These muscles were chosen due to their superficial nature and easy access which allowed data to be clean and reliable. Participant's skin was prepared and sensors were placed according to accepted standards and guidelines [16]. The signals from the force treadmill and EMG were acquired using a DAQ Board (Measurement Computing Corporation, Norton, MA) which fed the live voltage signal into LabVIEW (National Instruments, Austin, TX).

In LabVIEW, the live voltage signals from the DAQ Board were filtered through a 4th order bandpass and lowpass filter and then rectified [16]. Each individual muscle signal was multiplied by the fraction of muscle volume within a lower extremity from a previous imaging study [23]. The program used the ground reaction forces to signal heel strike and toe-off while numerically integrating the EMG signal [24]. This resulted in the quantity referred to as RAW, which is the unaltered summed muscle activity for each stride. After a pilot trial, it was observed that the negative stride conditions (-30%, -15%) were overestimated while the positive stride conditions (15%, 30%) were underestimated significantly compared to IC in the RAW data. A scaling coefficient calculation to approximate the cost-of-force (COF) was added to observe if its inclusion would provide a closer match to IC. This was obtained by taking the reciprocal of stride time from a three-stride moving average, which would decrease the muscle output estimation for the slower conditions with a longer stride time (-30%, -15%) and increase them for the faster ones with a quicker stride time (15%, 30%). The unaltered summed muscle activity, RAW, was multiplied by the COF coefficient separately to determine how they compared to each other in approximating MEE. This resulted in two quantities that were analyzed, the first being the unaltered summed muscle activity, RAW, and the second being RAW multiplied by the cost-of-force coefficient, referred to as COF. Throughout the data collection, a bar graph displayed the COF summed muscle activity per stride and the percentages of the individual muscle contributions for the previous three strides in real-time. The participants were told not to alter their walking based on the real-time display but match the audible metronome.

Following the data collection, metabolic energy expenditure was calculated from averaged gas exchange data over the last two minutes of each condition [25]. The average stride-by-stride muscle activity exported from LabVIEW was sorted by condition. The last 189 strides for each condition were used for data analysis.

To examine the qualitative relationship between MEE and EMG per stride, each subject's average ground truth MEE and summed total muscle activity per stride for each condition (-30%, -15%, PSF, +15%, +30%) were packaged together as the RAW unaltered totals and the COF product. Statistical analyses were performed in MATLAB (2021b, MathWorks, Natick, MA), R (R Core Team, 2017) and Excel®. To examine the qualitative relationships between datasets, orthogonal polynomial contrast analysis with ANOVA methods were utilized to examine which polynomial equation best represented the relationship of the summed total muscle activity and ground truth energy expenditure. As a surrogate measure we expect values for EMG obtained from an individual participant, or a function of these values, to be close to that individual's MEE value. What is considered a suitable tolerance between MEE and the surrogate measure will depend on the application. For this study, surrogate values needed to be within 10% of the MEE value. Another property of a surrogate measure is that it is close to the target value with high probability. With only five individuals this aspect could not be addressed. We began with the simplest surrogate, that of using EMG values. EMG values may stabilize earlier than MEE, but the required number of strides for this stabilization is unknown and can depend on experimental condition and the individual. The relationship between number of strides and the potential of EMG values to be used as surrogates was explored by making scatter plots with the difference between log EMG and log MEE values on the y-axis and number of strides on the x-axis. Plotting symbols of different colors were used to distinguish the individuals.

3. Results

All analyses were computed using the data from the ground truth energy expenditure calculated from IC and the EMG muscle activity per stride (Table 1). MEE had a U-shaped relationship, with the least amount of MEE at the PSF and increasing exponentially the further away the participant deviated from the PSF ($p = 0.015$, $R^2 = 0.090$ [linear]; $p < 0.001$, $R^2 = 0.966$ [quadratic]; $p = 0.676$, $R^2 = 0.984$ [cubic]) (Fig. 2). The average muscle activity per stride with the implemented COF coefficient had a similar U-shaped relationship ($p = 0.023$, $R^2 = 0.211$ [linear]; $p = 0.004$, $R^2 = 0.701$ [quadratic]; $p = 0.449$, $R^2 = 0.963$ [cubic]) (Fig. 2). MEE and COF was represented best by a quadratic equation, while the RAW unaltered totals ($p < 0.001$, $R^2 = 0.534$ [linear]; $p = 0.051$, $R^2 = 0.874$ [quadratic]; $p < 0.001$, $R^2 = 0.993$ [cubic]) was best represented by a cubic equation (Fig. S1).

The plots showed that for most conditions the EMG values stabilized after 100 strides, meaning there were ~89 strides left within the condition, and therefore not stabilizing faster than MEE (Figs. 3-4). These plots also showed considerable variability across the five individuals (Figs. 3-4). The EMG values did not stabilize in the range from -.10 to .10 for any conditions (Fig. 4), therefore absolute differences on the log scale, which correspond to the log of relative differences on the original scale, did not stabilize between 90.5% (= exp(-.10)*100%) and 110.5% (= exp(.10)*100%) of the MEE value.

These plots also showed that stabilized values for the five individuals were not centered at zero (Figs. 3-4). For many of the conditions, the EMG values were below their corresponding MEE values. If the stabilized values for all five individuals fell within a range of 0.2 (not necessarily centered at zero, i.e., -.10 to .10) then there is the possibility that an offset could be used to make these values into suitable surrogates. Ideally, the range would be less than 0.2 since the offset would be based on the data and so introduce additional variability. None of the plots had a range of stabilized values that was less than 0.57 (Table 2). The muscle groupings that stabilized in a range of 0.57 were MG-SOL, BF-SOL, BF-MG, and BF-VL-MG, only when multiplied by the COF coefficient (Fig. 4, Table 2).

4. Discussion

The purpose of this project was to determine feasibility of a method that estimates real-time energy expenditure with EMG signals by comparing it to IC. When looking at mean muscle activity per stride over individuals, our results indicate a promising relationship with MEE measured with IC, especially for summed muscle activity scaled by the inverse of stride time (i.e., COF). The COF ($R^2 = 0.701$) summed muscle activity had a U-shaped relationship across conditions, similar to MEE ($R^2 = 0.967$), which was expected (Fig. 2) [6]. The estimated changes in MEE from summed muscle activity with our data are similar to a different study which determined that breath-by-breath EMG intensity gives a reliable assessment of changes in metabolic power [17]. The RAW unaltered totals did not reflect the U-shaped curve, as they tended

Table 1
Average and standard deviation of breath-by-breath MEE and EMG muscle activation (cost of force = COF, unscaled = RAW) per stride.

Stride Frequency Condition	MEE (J/kg/m Net)	COF (V/s)	RAW (V/s)
-30%	3.43 ± 0.66	3.59 ± 0.61	4.94 ± 0.80
-15%	2.54 ± 0.48	2.71 ± 0.247	3.27 ± 0.31
PSF	2.08 ± 0.22	2.73 ± 0.21	2.97 ± 0.29
+15%	2.46 ± 0.12	3.14 ± 0.37	3.03 ± 0.57
+30%	3.32 ± 0.31	3.29 ± 0.40	2.97 ± 0.31

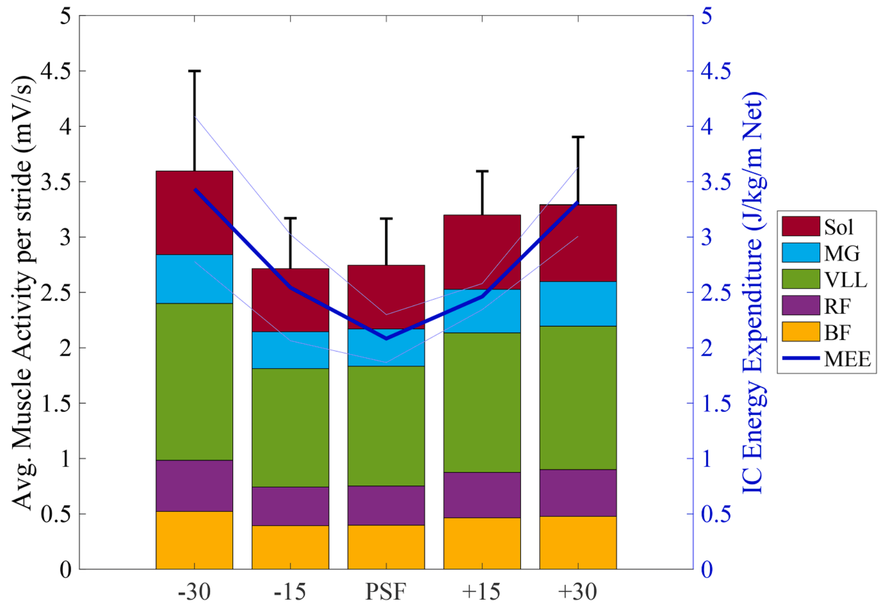

Fig. 2. Muscle Contribution to COF Average Summed Muscle Activity: Mean MEE and muscle activity at different stride frequencies. Shaded blue and error bars are ± 1 SD. COF summed muscle activity reflects U-shaped curve seen of MEE from IC, indicating a potential qualitative relationship.

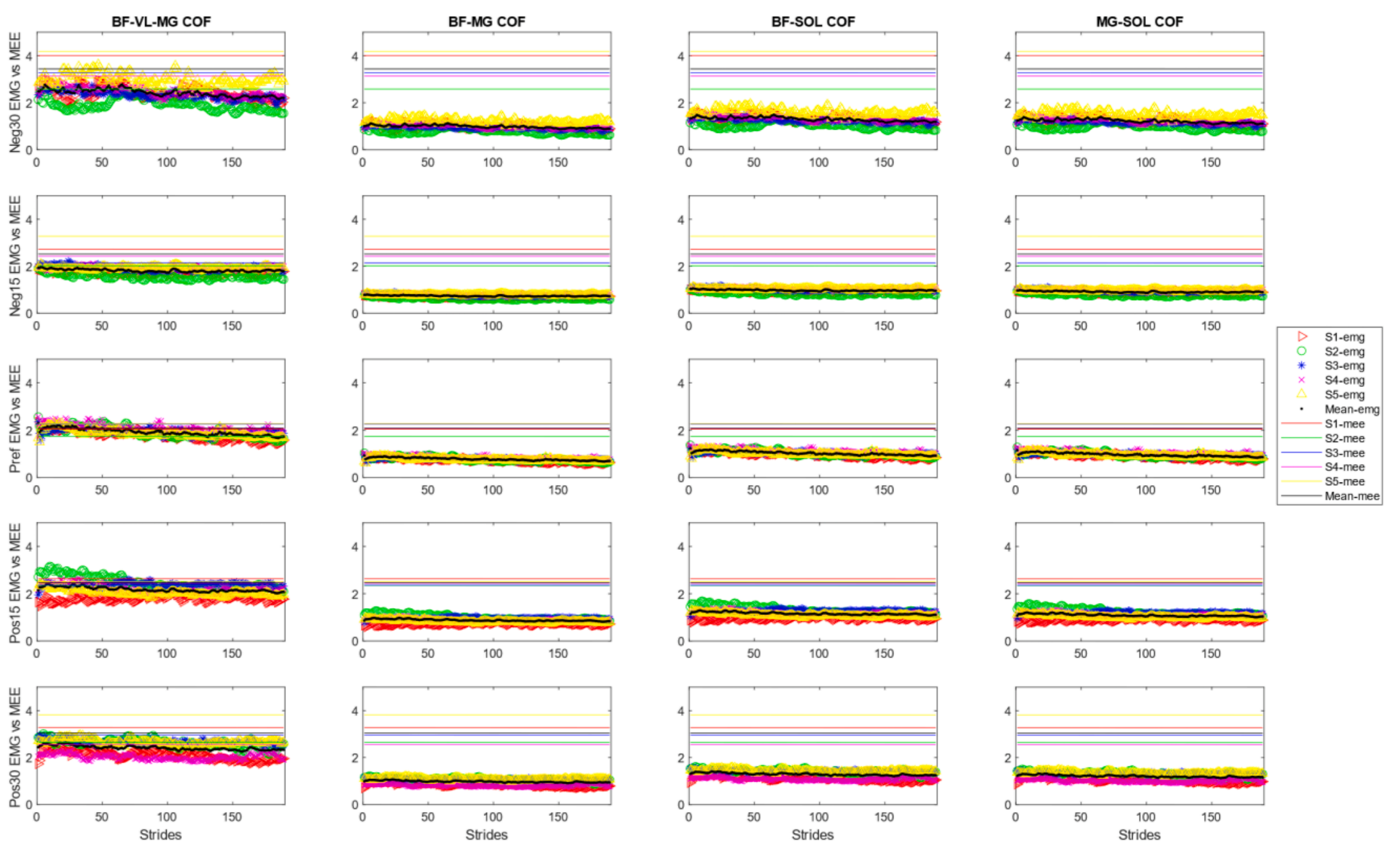

Fig. 3. Steady state MEE (solid line) and COF EMG by stride (dots) for four muscle combinations for individual participants (colors) and means (black). Each dot represents an individual stride. The EMG COF values underestimate the steady state MEE in most conditions and muscle combinations.

to overestimate the negative conditions (i.e., longer strides) and underestimate the positive conditions (i.e., shorter strides) (Fig. S1-2). The COF coefficient considered the amount of force needed to execute quicker movements and increased the values seen in the positive conditions, and decreased the values seen in the negative conditions.

While muscle activity per stride increases and decreases along with MEE, our results showed the variability in the relationship across individuals indicates that additional information is required to obtain a suitable approximation to the MEE value for an individual. We tried to account for the different energetic demands of each muscle by scaling muscles to relative volume within each leg. There may be other scaling factors, statistical methods such as multiple linear regression in real-

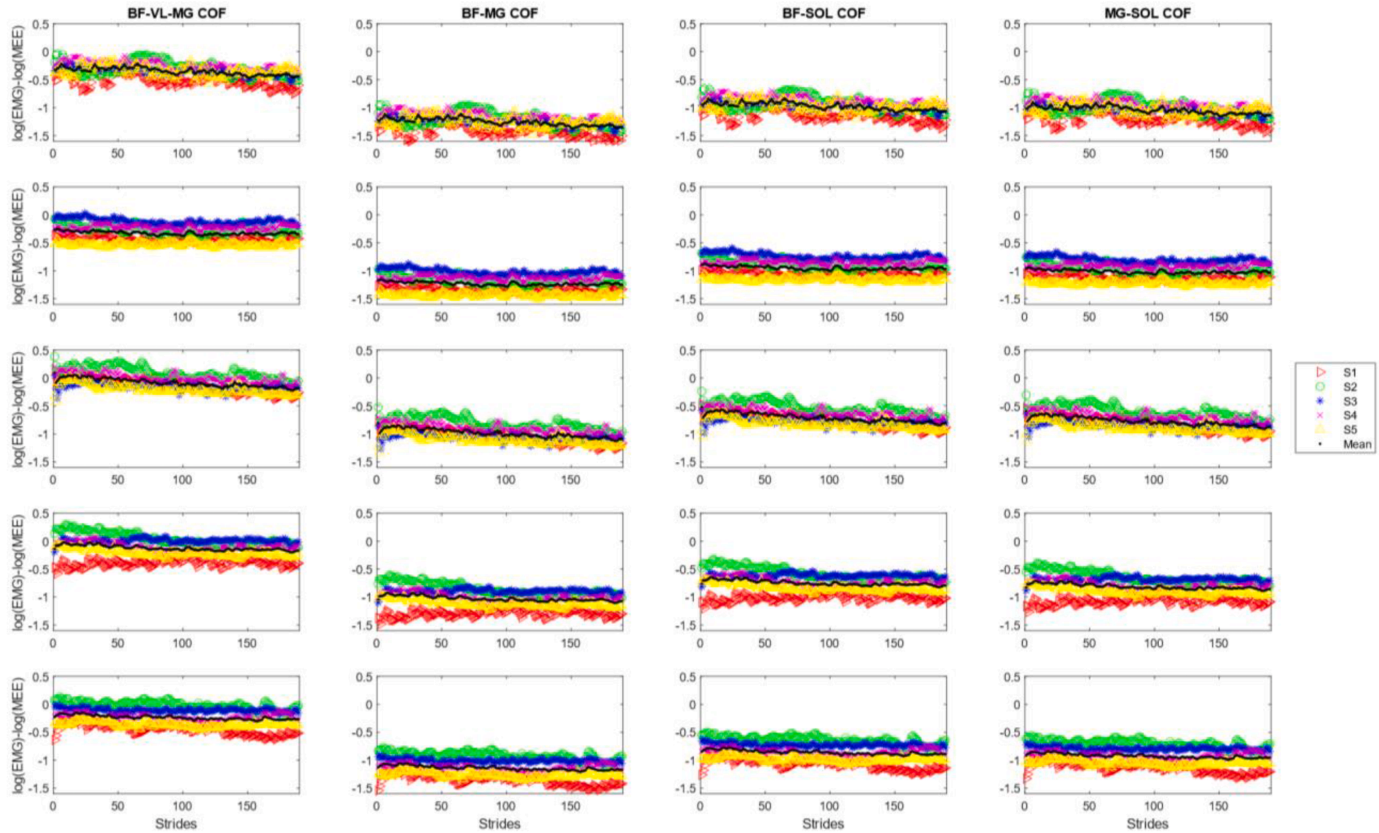

Fig. 4. Log differences of EMG and MEE for muscle combinations that had the lowest spread between individual participant data (0.57) and represent the closest quantitative relationship between EMG and MEE. Each dot is an individual stride, with inidividual participants (colored) and means (black). Each muscle combinations with the smallest range had at least one triceps surae muscle and three of the four were only two muscles.

time, or other forms of machine learning that this study did not consider to establish significantly similar quantitative values. The analysis shows that for many conditions, the EMG values stabilized for each of the individuals after a reasonable number of strides (~100). We also found that the variability among individuals was so great that the stabilized values cannot be used as surrogate measure which indicates surrogate values will need to include participant characteristics (such as sex) and/or that the experimental conditions (e.g., velocity) need to be adjusted to address differences among participants (such as height). Establishing a quantitative relationship could lead to better predictions of MEE in the real-world and avoid the limitations of IC in the laboratory, assuming that measuring muscle activity would result in a smaller time delay to attain steady state to quantify the MEE for a new walking task. However, it is possible that it would take longer than hoped, this is yet to be determined and leads to a future research goal.

After analyzing different combinations of muscle groups, we cannot confirm that larger sets of muscles would be better predictors of energy expenditure. However, this could mean that the muscles used in this project each contain valuable information about real-time energy expenditure, potentially implying that a small number of sensors would be needed to get a reliable qualitative relationship. The four muscle combinations with a spread of 0.57 (Fig. 4) all had at least one triceps surae muscle, and three of the four had only two muscles. The triceps surae is an important set of locomotor muscles [26] and having only two muscles with the best quantitative results indicate potential for less sensors being needed. A study that examined muscle activity tuning to different stride frequencies showed that peak EMG values from eight different muscles, including the five muscles used in this study, all demonstrated the U-shaped quadratic relationship across varying stride frequencies [27].

There were many limitations with this initial study, as this research served as a pilot study and provided the technical means to continue to research a relationship between MEE and EMG. Due to the nature of the study, researchers were provided with a small window of time to access the equipment needed to both develop the real-time program and collect participant data, and were not given any additional opportunities to collect data for more subjects. The sample size was smaller than needed to show validation of a reliable pattern of MEE across subjects and a larger scale study with more participants and other numerical considerations will need to be conducted to make any conclusive statements about the feasibility of developing a real-time EMG surrogate for MEE. We believe the findings are another step in trying to find real-time MEE surrogates and will be useful in designing a larger study. We did not account for the force-length and force-velocity properties of muscles and how elastic energy could be playing a role with different conditions. Walking at different stride frequencies at only one constant velocity was observed. Other factors, such as changing velocities, terrain, and movements were not represented in this study, which would be a more robust examination into the relationship between MEE and EMG. Additionally, all the participants were young and able-bodied, therefore not representative of populations with disabilities, which this research aims to benefit. Lastly, EMG is an inherently noisy signal that can be distorted by sensor sliding and electrical noise due to sweat and excess body tissue.

Future studies will have more participants with additional procedures included to capture rapidly changing stride frequency conditions. We will also use other statistical and mathematical methods, such as multiple linear regression or extraction of different EMG features to estimate MEE more accurately. An increased number of participants and different mathematical methods may answer remaining questions regarding the quantitative relationship between MEE and EMG muscle activity per stride, while also improving quantitative predictions. Once

Table 2
Spread of individual data showing the offset between max and min EMG and metabolic energy expenditure log differences after the 100th stride in column one of each condition, and the minimum (column two of each condition) and maximum (column three of each condition) percentage of EMG stabilization relative to metabolic energy expenditure for 30 muscle combinations with RAW and COF values. 12 combinations are bolded because they are the smallest spreads of individual data (0.57 and 0.58).

Muscle Combinations	Negative 30%			Negative 15%			Preferred			Positive 15%			Positive 30%			Means		
SOL COF	0.60	74.1	135.0	0.55	76.0	131.7	0.56	75.6	132.3	0.55	76.0	131.7	0.68	71.2	140.5	0.59	74.6	134.2
SOL	0.70	70.5	141.9	0.80	67.0	149.2	0.63	73.0	137.0	1.05	59.2	169.0	1.25	53.5	186.8	0.89	64.6	156.8
MG COF	**0.60**	**74.1**	**135.0**	**0.58**	**74.8**	**133.6**	**0.55**	**76.0**	**131.7**	**0.50**	**77.9**	**128.4**	**0.65**	**72.3**	**138.4**	**0.58**	**75.0**	**133.4**
MG	0.70	70.5	141.9	0.78	67.7	147.7	0.60	74.1	135.0	1.05	59.2	169.0	1.20	54.9	182.2	0.87	65.3	155.2
VL COF	**0.60**	**74.1**	**135.0**	**0.52**	**77.1**	**129.7**	**0.55**	**76.0**	**131.7**	**0.54**	**76.3**	**131.0**	**0.70**	**70.5**	**141.9**	**0.58**	**74.8**	**133.8**
VL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.05	59.2	169.0	1.25	53.5	186.8	0.87	65.2	155.7
RF COF	0.60	74.1	135.0	0.57	75.2	133.0	0.57	75.2	133.0	0.52	77.1	129.7	0.70	70.5	141.9	0.59	74.4	134.5
RF	0.67	71.5	139.8	0.87	64.7	154.5	0.60	74.1	135.0	1.02	60.0	166.5	1.15	56.3	177.7	0.86	65.3	154.7
BF COF	0.60	74.1	135.0	0.56	75.6	132.3	0.55	76.0	131.7	0.55	76.0	131.7	0.75	68.7	145.5	0.60	74.1	135.2
BF	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	3.15	20.7	483.1	1.25	53.5	186.8	1.29	57.5	218.5
MG-SOL COF	**0.60**	**74.1**	**135.0**	**0.55**	**76.0**	**131.7**	**0.53**	**76.7**	**130.3**	**0.53**	**76.7**	**130.3**	**0.65**	**72.3**	**138.4**	**0.57**	**75.1**	**133.1**
MG-SOL	0.70	70.5	141.9	0.78	67.7	147.7	0.60	74.1	135.0	1.00	60.7	164.9	1.20	54.9	182.2	0.86	65.6	154.3
VL-SOL COF	**0.60**	**74.1**	**135.0**	**0.55**	**76.0**	**131.7**	**0.55**	**76.0**	**131.7**	**0.55**	**76.0**	**131.7**	**0.65**	**72.3**	**138.4**	**0.58**	**74.8**	**133.7**
VL-SOL	0.70	70.5	141.9	0.40	81.9	122.1	0.60	74.1	135.0	1.05	59.2	169.0	1.28	52.7	189.6	0.81	67.7	151.5
VL-MG COF	0.60	74.1	135.0	0.55	76.0	131.7	0.57	75.2	133.0	0.55	76.0	131.7	0.68	71.2	140.5	0.59	74.5	134.4
VL-MG	0.67	71.5	139.8	0.79	67.4	148.4	0.63	73.0	137.0	1.00	60.7	164.9	1.20	54.9	182.2	0.86	65.5	154.5
RF-SOL COF	0.70	70.5	141.9	0.56	75.6	132.3	0.55	76.0	131.7	0.50	77.9	128.4	0.70	70.5	141.9	0.60	74.1	135.2
RF-SOL	0.65	72.3	138.4	0.78	67.7	147.7	0.60	74.1	135.0	1.03	59.8	167.4	1.20	54.9	182.2	0.85	65.7	154.1
RF-MG COF	0.58	74.8	133.6	0.58	74.8	133.6	0.55	76.0	131.7	0.55	76.0	131.7	0.70	70.5	141.9	0.59	74.4	134.5
RF-MG	0.68	71.2	140.5	0.75	68.7	145.5	0.60	74.1	135.0	1.05	59.2	169.0	1.25	53.5	186.8	0.87	65.3	155.4
RF-VL COF	**0.60**	**74.1**	**135.0**	**0.55**	**76.0**	**131.7**	**0.55**	**76.0**	**131.7**	**0.57**	**75.2**	**133.0**	**0.65**	**72.3**	**138.4**	**0.58**	**74.7**	**133.9**
RF-VL	0.69	70.8	141.2	0.55	76.0	131.7	0.60	74.1	135.0	1.00	60.7	164.9	1.20	54.9	182.2	0.81	67.3	151.0
BF-SOL COF	**0.58**	**74.8**	**133.6**	**0.53**	**76.7**	**130.3**	**0.55**	**76.0**	**131.7**	**0.54**	**76.3**	**131.0**	**0.65**	**72.3**	**138.4**	**0.57**	**75.2**	**133.0**
BF-SOL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.00	60.7	164.9	1.15	56.3	177.7	0.84	66.0	153.0
BF-MG COF	**0.60**	**74.1**	**135.0**	**0.55**	**76.0**	**131.7**	**0.50**	**77.9**	**128.4**	**0.55**	**76.0**	**131.7**	**0.65**	**72.3**	**138.4**	**0.57**	**75.2**	**133.0**
BF-MG	0.70	70.5	141.9	0.78	67.7	147.7	0.63	73.0	137.0	1.05	59.2	169.0	1.20	54.9	182.2	0.87	65.0	155.6
BF-VL COF	0.58	74.8	133.6	0.55	76.0	131.7	0.55	76.0	131.7	0.55	76.0	131.7	0.70	70.5	141.9	0.59	74.6	134.1
BF-VL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.05	59.2	169.0	1.30	52.5	191.6	0.88	64.9	156.6
BF-RF COF	**0.60**	**74.1**	**135.0**	**0.53**	**76.7**	**130.3**	**0.55**	**76.0**	**131.7**	**0.56**	**75.6**	**132.3**	**0.65**	**72.3**	**138.4**	**0.58**	**74.9**	**133.5**
BF-RF	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.03	59.8	167.4	1.25	53.5	186.8	0.87	65.3	155.3
VL-MG-SOL COF	0.58	74.8	133.6	0.55	76.0	131.7	0.55	76.0	131.7	0.55	76.0	131.7	0.70	70.5	141.9	0.59	74.6	134.1
VL-MG-SOL	0.70	70.5	141.9	0.75	68.7	145.5	0.65	72.3	138.4	1.05	59.2	169.0	1.25	53.5	186.8	0.88	64.8	156.3
RF-MG-SOL COF	0.60	74.1	135.0	0.53	76.7	130.3	0.57	75.2	133.0	0.55	76.0	131.7	0.70	70.5	141.9	0.59	74.5	134.4
RF-MG-SOL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.05	59.2	169.0	1.30	52.2	191.6	0.88	64.9	156.6
RF-VL-SOL COF	**0.58**	**74.8**	**133.6**	**0.55**	**76.0**	**131.7**	**0.53**	**76.7**	**130.3**	**0.55**	**76.0**	**131.7**	**0.70**	**70.5**	**141.9**	**0.58**	**74.8**	**133.8**
RF-VL-SOL	0.70	70.5	141.9	0.78	67.7	147.7	0.63	73.0	137.0	1.05	59.2	169.0	1.25	53.5	186.8	0.88	64.8	156.5
RF-VL-MG COF	0.58	74.8	133.6	0.57	75.2	133.0	0.55	76.0	131.7	0.57	75.2	133.0	0.70	70.5	141.9	0.59	74.3	134.6
RF-VL-MG	0.73	69.4	144.1	0.75	68.7	145.5	0.60	74.1	135.0	1.02	60.0	166.5	1.35	50.9	196.4	0.89	64.6	157.5
BF-MG-SOL COF	0.58	74.8	133.6	0.57	75.2	133.0	0.55	76.0	131.7	1.10	57.7	173.3	0.70	70.5	141.9	0.70	70.8	142.7
BF-MG-SOL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.00	60.7	164.9	1.25	53.5	186.8	0.86	65.5	154.8
BF-VL-SOL COF	0.60	74.1	135.0	0.53	76.7	130.3	0.55	76.0	131.7	0.55	76.0	131.7	0.70	70.5	141.9	0.59	74.6	134.1
BF-VL-SOL	0.68	71.2	140.5	0.75	68.7	145.5	0.60	74.1	135.0	1.03	59.8	167.4	1.20	54.9	182.2	0.85	65.7	154.1

(*continued on next page*)

Table 2 (*continued*)

Muscle Combinations	Negative 30%			Negative 15%			Preferred			Positive 15%			Positive 30%			Means		
BF-VL-MG COF	**0.58**	**74.8**	**133.6**	**0.55**	**76.0**	**131.7**	**0.53**	**76.7**	**130.3**	**0.55**	**76.0**	**131.7**	**0.65**	**72.3**	**138.4**	**0.57**	**75.1**	**133.1**
BF-VL-MG	0.70	70.5	141.9	0.80	67.0	149.2	0.63	73.0	137.0	1.03	59.8	167.4	1.25	52.7	189.6	0.89	64.6	157.0
BF-RF-SOL COF	**0.55**	**76.0**	**131.7**	**0.57**	**75.2**	**133.0**	**0.55**	**76.0**	**131.7**	**0.55**	**76.0**	**131.7**	**0.70**	**70.5**	**141.9**	**0.58**	**74.7**	**134.0**
BF-RF-SOL	0.70	70.5	141.9	0.78	67.7	147.7	0.57	75.2	133.0	1.05	59.2	169.0	1.25	53.5	186.8	0.87	65.2	155.7
BF-RF-MG-COF	0.60	74.1	135.0	0.55	76.0	131.7	0.55	76.0	131.7	0.55	76.0	131.7	0.75	68.7	145.5	0.60	74.1	135.1
BF-RF-MG	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.00	60.7	164.9	1.25	53.5	186.8	0.86	65.5	154.8
BF-RF-VL COF	0.60	74.1	135.0	0.55	76.0	131.7	0.53	76.7	130.3	0.55	76.0	131.7	0.70	70.5	141.9	0.59	74.6	134.1
BF-RF-VL	0.70	70.5	141.9	0.78	67.7	147.7	0.60	74.1	135.0	1.03	59.8	167.4	1.28	52.7	189.6	0.88	64.9	156.3
RF-VL-MG-SOL COF	0.60	74.1	135.0	0.55	76.0	131.7	0.56	75.6	132.3	0.55	76.0	131.7	0.68	71.2.	140.5	0.59	74.6	134.2
RF-VL-MG-SOL	0.70	70.5	141.9	0.80	67.0	149.2	0.60	74.1	135.0	1.05	59.2	169.0	1.25	53.5	186.8	0.88	64.9	156.4
BF-VL-MG-SOL COF	0.58	74.8	133.6	0.56	75.9	132.3	0.55	76.0	131.7	0.60	74.1	135.0	0.70	70.5	141.9	0.60	74.2	134.9
BF-VL-MG-SOL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.00	60.7	164.9	1.25	53.5	186.8	0.86	65.5	154.8
BF-RF-VL-SOL COF	0.60	74.1	135.0	0.60	74.1	135.0	0.55	76.0	131.7	0.55	76.0	131.7	0.70	70.5	141.9	0.60	74.1	135.0
BF-RF-VL-SOL	0.70	70.5	141.9	0.75	68.7	145.5	0.60	74.1	135.0	1.00	60.7	164.9	1.25	53.5	186.8	0.86	65.5	154.8
BF-RF-VL-MG COF	0.60	74.1	135.0	0.56	75.6	132.3	0.55	76.0	131.7	0.60	74.1	135.0	0.70	70.5	141.9	0.60	74.0	135.2
BF-RF-VL-MG	0.67	71.5	139.8	0.75	68.7	145.5	0.60	74.1	135.0	1.02	60.0	166.5	1.25	53.5	186.8	0.86	65.6	154.7
BF-RF-VL-MG-SOL COF	**0.60**	**74.1**	**135.0**	**0.55**	**76.0**	**131.7**	**0.55**	**76.0**	**131.7**	**0.55**	**76.0**	**131.7**	**0.65**	**72.3**	**138.4**	**0.58**	**74.8**	**133.7**
BF-RF-VL-MG-SOL	0.69	70.8	141.2	0.78	67.7	147.7	0.60	74.1	135.0	1.03	59.8	167.4	1.28	52.7	189.6	0.88	65.0	156.2

validation of the method is reached with able-bodied participants, we hope to use this method with people who have disabilities, to examine MEE with rapidly changing gait strategies. Trying different gait strategies in a short period of time may lead to finding the best gait pattern more efficiently. Extending this research to movements such as running, lifting, jumping, and other everyday occurrences would be beneficial and make this method more generalizable to the real-world.

Implications of a real-time energy expenditure feedback system are extensive for people with disabilities. This technology could be integrated into a wearable sensor taken outside a lab setting, collecting energy cost information about everyday movements. Clinicians could have access to this data and make recommendations that would lessen metabolic energy costs. It may aide in the development of exoskeletons or powered protheses by showing the macroscopic effects of the device on the body. By making movements more economical, people will hopefully move more. Increased physical activity lowers the risk for conditions such as cardiovascular disease, joint degradation, diabetes, and depression, among many others [28–30]. This proof-of-concept study established a method with reasonable preliminary results for a real-time energy expenditure feedback system that could be used to significantly improve the health and quality of life for people with disabilities.

5. Declarations

The following additional information is required for submission. Please note that this form runs over two pages and failure to respond to these questions/statements will mean your submission will be returned to you. If you have nothing to declare in any of these categories then this should be stated.

Funding

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Ethical approval

The study was approved by the East Carolina University Institutional Review Board (UMCIRB 21-001504).

Declaration of Competing Interest

The authors do not have any competing interests.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.medengphy.2022.103899.

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Further reading

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