Correlation of spatiotemporal and EMG measures with Lower Extremity Fugl-Meyer Assessment score in post-stroke walking*

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Abstract. Lower Extremity Fugl-Meyer Assessment (FMA-LE) is recommended as the primary outcome for assessing motor function in post-stroke population. However, the subjectivity, dependency on professional experience, and time-consuming visual inspection by healthcare professionals limit the use of FMA-LE in clinical practice. Contrarily to clinical scales, sensor-based assessments can automatically provide objective measurements of motor function. This work advances literature by evaluating the Spearman correlation between the FMA-LE clinical scores and both spatiotemporal and electromyographic (EMG) measures, acquired during different mobility walking tasks (self-selected speed, maximum speed, maximum cadence, maximum step length, and maximum step height). Data were extracted from ARRA dataset, including 27 post-stroke participants. The results showed that step length ($0.44 \leq r \leq 0.60$), stride time ($-0.48 \leq r \leq -0.40$), and cadence ($0.40 \leq r \leq 0.46$) spatiotemporal measures, and peak power frequency (PKF) EMG measure of gluteus medius ($r = 0.42$), lateral hamstring ($0.40 \leq r \leq 0.46$), and vastus medialis ($0.42 \leq r \leq 0.45$) muscles revealed significant strong correlations in multiple walking tasks. Overall, spatiotemporal measures presented higher correlations with FMA-LE than EMG measures. These findings are promising for future research to develop artificial intelligence methods to estimate the Lower FMA clinical scores for motor assessment, maximizing its use in clinical practice.

Keywords: Healthcare Automation, Human Motor Assessment, Sensor-based Assessment.

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1 Introduction

Stroke affects worldwide 14 million people per year with an economic impact of €64 billion [1–3]. The epidemiological perspectives of stroke in Europe for the 21st century indicate that the aging of the population would lead to an incidence increase, being more people left with long-term disabilities [4, 5]. Muscle paralysis or partial loss of muscle strength, postural instability, and impaired functional motor ability are post-stroke sequelae addressed during physical rehabilitation [6].

Clinical scales such as Fugl-Meyer Assessment (FMA) scale are essential for diagnostic and therapeutic purposes in clinical practice once they allow a common language between healthcare professionals that facilitates comparisons of patients and treatments and, thus, guides critical treatment choices for rehabilitation [7]. Moreover, in research, clinical scales are helpful as standard measures, allowing to test the efficacy of a particular intervention and sensor-based assessments that in the future can be used in clinical practice [7].

Lower Extremity FMA (FMA-LE) is usually applied in research [8] due to being recommended as the primary outcome to assess motor function in populations with stroke [9]. It is a stroke-specific performance-based impairment score that evaluates lower limb motor function by visually inspecting multiple motor tasks instructed to the patient [10–12]. It results in a time-consuming procedure for healthcare professionals [10–13]. Although it presents excellent inter- and intra-rater reliability, the clinical scale is dependent on professional experience, what may introduce subjectivity, asking for possible improvements in clinical practice [10–13].

Sensors such as force plates, optical motion capture, and electromyographic (EMG) systems are usually applied in gait analysis settings, allowing an objective evaluation of human motor performance [14]. Contrarily to clinical scales, sensors do not rely on intensive visual inspection and return quantitative objective measurements [14]. In this manner, current literature can benefit from investigating potential correlations between objective sensor-based measures during a single task of walking with FMA-LE score to maximize its clinical use.

Previous studies have investigated correlations between sensor-based measurements and FMA but focuses on the upper extremity [15–18]. As appointed by Rech et al. [19], fewer studies are available focusing on Lower Extremity FMA. Moreover, the existing studies [19, 20] are limited to spatiotemporal measurements, not including physiological ones such as EMG, and did not study other motor tasks than walking at self-selected speed.

This work addresses these open aspects. It aims to evaluate the correlation between sensor-based spatiotemporal and EMG measures acquired during different mobility walking tasks (self-selected speed, maximum speed, maximum cadence, maximum step length, and maximum step height) with FMA-LE clinical scores. It attempts to answer the following research question: “How are objective spatiotemporal and EMG measures of post-stroke walking correlated with FMA-LE scores?”. The paper outcomes will contribute to maximizing the use of FMA-LE in clinical practice to support clinical decisions concerning diagnosis and treatment prescription towards an efficient recovery of stroke survivors.

The paper is organized as follows. Firstly, the post-stroke participants, the procedures undertaken during the clinical protocol, and the FMA-LE are described. Secondly, the EMG and spatiotemporal sensor-based measures are identified, and the data processing involved in deriving EMG-based and spatiotemporal measures is detailed. Thirdly, the statistical methods are identified, and the resulting correlations are presented and discussed.

2 Methods

2.1 Participants

Data for this paper were extracted from ARRA dataset [21]. It includes 27 post-stroke participants (9 female, 60.15±12.08 years, 92.07±18.72 kg, 22.85±6.95 FMA-LE score) recruited from the Medical University of South Carolina (USA). All participants provided written informed consent, and the Institutional Review Board approved the protocol. The following subject inclusion criteria were applied: (1) a history of single unilateral stroke more than six months before the study, (2) ability to walk over 10 m on a level surface, (3) free of significant lower extremity joint pain, contractures, range of motion limitations, and significant sensory deficits, (4) walk daily in the home, (5) with no severe cognitive deficits, (6) no significant cardiovascular impairments contraindicative to walking.

2.2 Procedures

The participants were instructed to walk during three 30-s trials on an instrumented treadmill at their self-selected walking speed (SS), maximum speed (FC), maximum cadence (QS), maximum step length (LS), and maximum step height (HS), being these mobility tasks randomly executed.

Clinical measures were obtained through the FMA-LE, performed once per participant before treadmill walking. Sensor-based measures were collected during walking. Kinematic data were recorded at 120 Hz from a 12-camera motion capture system (PhaseSpace, CA) using reflective markers placed on limbs and torso following a modified Helen Hayes marker set. Treadmill's force plates allowed the acquisition of 3D ground reaction forces (GRF) at 2000 Hz. Kinematic and GRF data were filtered using a fourth-order Savitzky-Golay least-square polynomial filter and resampled at 100 Hz. Spatiotemporal measures were derived from kinematic and GRF data. EMG data were acquired at 1000 Hz (Motion Lab Systems, LA) from the paretic tibialis anterior (TA), soleus (SO), medial gastrocnemius (MG), vastus medialis (VM), rectus femoris (RF), medial hamstrings (MH), lateral hamstrings (LH), and gluteus medius (GM) muscles. EMG average cycle timing curves were filtered with a zero-lag, fourth-order, band-pass Butterworth filter between 4 and 40 Hz. Then, each EMG signal was rectified and normalized to its peak value during each trial.

2.3 Clinical Measures: Lower Fugl-Meyer Assessment

The FMA-LE evaluates stroke victims' lower limb motor function, including domains of movement, coordination, speed, and reflex action of the hip, knee, and ankle joints [10–12]. For the movement domain, the participants are instructed to perform volitional movement within synergies in a supine position, mixing synergies in a sitting position, and with little or no synergy in a standing position [12]. For the coordination and speed domains, the participants are asked to move the heel to the kneecap of the opposite leg five times as fast as possible in a supine position [12]. Items are scored on an ordinal scale of 0 (cannot perform/high disability), 1 (partial disability), and 2 (no disability) [12]. Overall motor scores range from 0 (hemiparetic) to a maximum of 34 (healthy motor performance) for the lower extremity [12]. According to Kwong et. al, low and high disability is considered if FMA-LE $\geq$ 21 and FMA-LE < 21, respectively [23].

2.4 Sensor-based Measures and Data Processing

Spatiotemporal Measures.

ARRA dataset provides spatiotemporal parameters for each gait cycle derived from kinematic and GRF data, including non-paretic (NP) and paretic (P) step and stride length, stride time, and cadence. Step and stride lengths are the distance between the point of initial contact of one foot and the point of initial contact of the opposite and same foot, respectively, during walking [25]. Stride time is the amount of time between the initial contact of one foot and the initial contact of the same foot during walking [25]. Cadence is the number of steps performed per minute of walking [25].

EMG Measures.

ARRA dataset provides normalized and rectified EMG curves for each trial and muscle. From these curves, we computed mean, median and peak power frequencies, since EMG-based frequency domain features are widely used [24].

Mean frequency, *MNF*, was calculated as a ratio between the sum of the product of the EMG power spectrum intensity, *P*, and the frequency, *f*, and the sum of the power spectrum intensity (Eq. 1) [24].

$$MNF = \frac{\sum_{j=1}^{M} P_j \times f_j}{\sum_{j=1}^{M} P_j}, \quad (1)$$

where *j* is a frequency bin, and *M* is the length of the frequency bin.

Median frequency, *MDF*, was determined as the frequency at which the EMG power spectrum intensity, *P*, is divided into two regions with equal amplitude (Eq. 2) [24].

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j \quad (2)$$

Peak frequency, *PKF*, consists of frequency at which the maximum power occurs (Eq. 3) [24].

$$PKF = \max(P_j), j = 1, \dots, M \quad (3)$$

2.5 Statistical Analysis

Shapiro-Wilk tests were used to evaluate the normality of sensor-based measurements. Spearman's correlation coefficients, *r*, were assessed to verify the correlation between FMA-LE scores and sensor-based measures for parametric and non-parametric variables. The strength of correlations was interpreted as a negligible relationship if *r*=0.01-0.19, weak if *r*=0.20-0.29, moderate if *r*=0.30-0.39, strong if *r*=0.40-0.69, and very strong if *r*≥0.7 [26]. The Spearman's correlation *p*-value was analyzed to determine if the correlation has a statistically significant meaning, occurring when the *p*-value < 0.05 (significance level). Statistical analyses were conducted using IBM SPSS software version 26.0 (IMP Corp, USA).

3 Results

3.1 Spatiotemporal Measures Correlated with Lower Fugl-Meyer Assessment Scores

Table 1 presents the correlation results between spatiotemporal measures and FMA-LE scores. All correlations were statistically significant (p-value $\leq$ 0.01) with the exception for P step length in QS task. NP step length, paretic stride time, and cadence were highlighted as strongly correlated spatiotemporal measures ($0.40 \leq |r| \leq 0.60$) with FMA-LE during all mobility tasks. The stride length measure only did not show strong correlations for QS task ($0.43 \leq r \leq 0.47$), while the P step length only revealed strong correlations for the LS task ($r = 0.42$).

Moreover, we observed that as the FMA-LE increased, meaning a reduced disability level, the P stride time decreased (negative correlation), while the NP step length and cadence measures increased (positive correlation) (Table S1 from Supplementary Material).

3.2 EMG Measures Correlated with Lower Fugl-Meyer Assessment Scores

Table 2 presents the correlation results between EMG measures and FMA-LE scores for each mobility walking task. Results indicate that the correlations vary according to the mobility tasks. For the SS, the MNF of soleus, MDF and PKF of vastus medialis and lateral hamstring, PKF of medial gastrocnemius, hamstring, and rectus femoris, and all EMG measures from gluteus medius showed statistically significant correlations with FMA-LE scores (p-value $\leq$ 0.02). The stronger ones are from lateral hamstring and gluteus medius ($0.42 \leq r \leq 0.44$), being that the MDF and PKF lateral hamstring and PKF gluteus medius increased with the increase of FMA-LE score (Table S2 from Supplementary Material).

Table 1. Spearman's correlation coefficients and related *p*-values, *r* (*p*-value), for each spatiotemporal measure during each mobility walking task (SS, FC, QS, LS, HS) correlated with FMA-LE scores. Darker orange indicates a stronger correlation coefficient. Statistically significant correlations (*p*-value<0.05) are indicated with *

Spatiotemporal measure	Mobility walking task				
	SS	FC	QS	LS	HS
P stride length	0.47* (<0.01)	0.44* (<0.01)	0.34* (<0.01)	0.44* (<0.01)	0.45* (<0.01)
NP stride length	0.47* (<0.01)	0.44* (<0.01)	0.33* (<0.01)	0.44* (<0.01)	0.43* (<0.01)
P step length	0.33* (<0.01)	0.31* (0.01)	0.16 (0.16)	0.42* (<0.01)	0.29* (0.01)
NP step length	0.60* (<0.01)	0.51* (<0.01)	0.46* (<0.01)	0.44* (<0.01)	0.51* (<0.01)
P stride time	-0.42* (<0.01)	-0.40* (<0.01)	-0.48* (<0.01)	-0.41* (<0.01)	-0.43* (<0.01)
Cadence	0.42* (<0.01)	0.40* (<0.01)	0.46* (<0.01)	0.41* (<0.01)	0.43* (<0.01)

Intended for the FC mobility task, the PKF of tibialis anterior and medial gastrocnemius, MNF and PKF of soleus, MDF and PKF of gluteus medius, lateral and medial hamstring, and all EMG measures from vastus medialis revealed statistically significant correlations (p-value $\leq$ 0.03). The strong ones are PKF of medial gastrocnemius and vastus medialis ($0.42 \leq r \leq 0.45$), presenting positive correlations (Table S2 from Supplementary Material).

Regarding the QS, the PKF soleus, MNF and PKF of rectus femoris, MDF and PKF of medial gastrocnemius and hamstring, and all EMG measures of vastus medialis, lateral hamstring, and gluteus medius are statistically significant correlated with FMA-LE scores (p-value $\leq$ 0.04). The MDF and PKF measures of vastus medialis and lateral hamstring muscles and the PKF of gluteus medius ($0.40 \leq r \leq 0.42$) are the stronger correlations, all positively correlated with FMA-LE scores.

For the LS mobility task, the MNF of medial gastrocnemius and hamstring muscles, MNF and MDF soleus, and PKF of tibialis anterior, lateral hamstring, and gluteus medius are statistically significant correlated with FMA-LE scores. The MNF measure of soleus is the stronger one ($r = -0.45$), decreasing as the FMA-LE score increases (Table S2 from Supplementary Material).

Concerning the HS, the statistically significant correlated EMG measures are MNF soleus, MDF and PKF gluteus medius, PKF from tibialis anterior, medial gastrocnemius and hamstring, and all EMG measures from vastus medialis and lateral hamstring (p-value $\leq$ 0.02). The strong correlations are from MDF and PKF vastus medialis and lateral hamstring ($0.40 \leq r \leq 0.46$), being positively correlated with FMA-LE scores (Table S2 from Supplementary Material).

Table 2. Spearman's correlation coefficients and related *p*-values, *r* (*p*-value), for each EMG measure during each mobility walking task (SS, FC, QS, LS, HS) correlated with FMA-LE scores. Darker orange indicates a stronger correlation coefficient. Statistically significant correlations (*p*-value<0.05) are indicated with *

EMG measure	Mobility walking task				
	SS	FC	QS	LS	HS
MNF tibialis anterior	0.12 (0.33)	0.09 (0.42)	0.18 (0.13)	-0.16 (0.18)	0.10 (0.42)
MDF tibialis anterior	0.15 (0.22)	0.12 (0.29)	0.09 (0.45)	0.02 (0.86)	0.16 (0.19)
PKF tibialis anterior	0.19 (0.12)	0.28* (0.02)	0.13 (0.27)	0.32* (<0.01)	0.35* (<0.01)
MNF soleus	-0.28* (0.02)	-0.38* (<0.01)	-0.12 (0.30)	-0.45* (<0.01)	-0.30* (0.01)
MDF soleus	-0.03 (0.81)	0.12 (0.29)	0.20 (0.09)	-0.27* (0.02)	0.02 (0.89)
PKF soleus	0.19 (0.10)	0.28* (0.01)	0.37* (<0.01)	0.07 (0.55)	0.19 (0.10)
MNF medial gastrocnemius	-0.17 (0.15)	-0.14 (0.25)	-0.09 (0.45)	-0.32* (<0.01)	-0.17 (0.14)
MDF medial gastrocnemius	0.22 (0.06)	0.21 (0.07)	0.24* (0.04)	-0.08 (0.49)	-0.11 (0.34)
PKF medial gastrocnemius	0.28* (0.02)	0.42* (<0.01)	0.35* (<0.01)	0.23 (0.05)	0.38* (<0.01)
MNF vastus medialis	0.20 (0.09)	0.32* (<0.01)	0.37* (<0.01)	-0.05 (0.68)	0.26* (0.02)
MDF vastus medialis	0.32* (0.01)	0.36* (<0.01)	0.40* (<0.01)	0.14 (0.22)	0.40* (<0.01)
PKF vastus medialis	0.30* (0.01)	0.45* (<0.01)	0.42* (<0.01)	0.21 (0.06)	0.42* (<0.01)
MNF rectus femoris	0.14 (0.26)	-0.06 (0.60)	0.26* (0.03)	-0.14 (0.24)	-0.03 (0.82)
MDF rectus femoris	0.03 (0.82)	-0.14 (0.23)	0.20 (0.10)	-0.13 (0.26)	-0.02 (0.84)
PKF rectus femoris	0.24* (0.04)	0.02 (0.88)	0.36* (<0.01)	0.13 (0.26)	0.17 (0.16)
MNF lateral hamstring	0.17 (0.15)	0.16 (0.18)	0.35* (<0.01)	-0.13 (0.27)	0.27* (0.02)
MDF lateral hamstring	0.43* (<0.01)	0.35* (<0.01)	0.40* (<0.01)	0.11 (0.37)	0.42* (<0.01)
PKF lateral hamstring	0.44* (<0.01)	0.35* (<0.01)	0.40* (<0.01)	0.27* (0.02)	0.46* (<0.01)
MNF medial hamstring	0.03 (0.79)	0.10 (0.38)	0.13 (0.26)	-0.26* (0.03)	-0.05 (0.64)

EMG measure	Mobility walking task				
	SS	FC	QS	LS	HS
MDF medial hamstring	0.20 (0.09)	0.24* (0.03)	0.25* (0.03)	-0.14 (0.24)	0.01 (0.92)
PKF medial hamstring	0.28* (0.02)	0.34* (<0.01)	0.37* (<0.01)	0.19 (0.11)	0.30* (0.01)
MNF gluteus medius	0.28* (0.02)	0.05 (0.67)	0.26* (0.03)	-0.08 (0.49)	0.23 (0.05)
MDF gluteus medius	0.37* (<0.01)	0.24* (0.03)	0.36* (<0.01)	0.07 (0.56)	0.25* (0.03)
PKF gluteus medius	0.42* (<0.01)	0.33* (<0.01)	0.42* (<0.01)	0.35* (<0.01)	0.36* (<0.01)

4 Discussion

This work aims to describe how spatiotemporal and EMG measures are correlated with FMA-LE clinical scores to complement this clinical scale with significant and strong correlated objective measures. The founded correlations may foster the use of spatiotemporal and EMG measures in clinical practice to objectively guide critical treatment choices for post-stroke rehabilitation, personalizing the rehabilitation program according to the patient's disability level.

Answering the research question, both spatiotemporal and EMG measures revealed statistically significant correlations with FMA-LE scores, indicating that their monotony is linked. In fact, spatiotemporal measures achieved more strength correlation coefficients (0.60 and 0.46 are the maximum correlation coefficients for spatiotemporal and EMG measures, respectively) than EMG measures. These maximum values are related to step length and PKF lateral hamstring during SS and HS walking tasks, respectively. However, the lateral hamstring muscle also showed a stronger correlation for the SS mobility walking task (r = 0.44). It should be noted that spatiotemporal measures have the advantage of not implicating a time-consuming subject preparation as EMG measures because it is not needed a skin preparation procedure [8]. However, both spatiotemporal and EMG measures proved to be suitable for validating the impact of rehabilitation robotics such as lower limb exoskeletons in stroke population's disability level, and for personalizing the robot's assistance according to user's needs.

Concerning spatiotemporal measures correlated with FMA-LE scores, the disability level of stroke survivors decreases as long as they can step more times per minute (increased cadence) and perform longer and faster steps (increased step and stride length and reduced stride time), justifying why these measures are used for biofeedback training in current research [27]. Rech et al. also obtained a significant correlation for cadence (r = 0.58), stride length (r = 0.44), and step length (r = 0.36) [19].

Regarding EMG measures correlated with FMA-LE scores, although the lateral hamstring revealed a stronger correlation during the SS mobility walking task, the gluteus medius also presented this behavior (r = 0.42), being both the stronger corre-

lated muscles. However, for faster speed walking (FC mobility task), the medial gastrocnemius and vastus lateralis (strong correlation strength) overcome lateral hamstring and gluteus medius (moderate correlation strength), indicating that speed changes muscle activation pattern as announced in [28]. During maximum cadence walking, lateral hamstring and gluteus medius are also highlighted as strong correlations in adjunction to the vastus medialis muscle. The soleus muscle exhibited a strong correlation only for the LS, while the tibialis anterior, rectus femoris, and medial hamstring are not strongly correlated with FMA-LE scores during any mobility walking task. On the other hand, gluteus medius (SS and QS tasks), lateral hamstring (SS, QS, and HS tasks), and vastus medialis (FC, QS, and HS tasks) revealed strong correlations in multiple mobility tasks. Therefore, the correlations between EMG measures with FMA-LE clinical scores innovatively explored in this work showed dependency on the mobility walking task.

Regardless of the mobility task and muscle studied, the PKF EMG-based feature demonstrated more correlations than MDF followed by MNF, being usually positively correlated with FMA-LE scores, as mentioned in [29]. Along these lines, an increase in clinical score occurs for increased mean, median, and peak power frequencies.

Moreover, based on achieved results, we can identify the most appropriate walking task to collect clinical meaningful spatiotemporal and EMG measures. Considering spatiotemporal measures, the mobility walking task presenting the highest number of significant strong correlations is LS (6 significant strong correlations), followed by SS, FC, and HS (5 significant strong correlations), and then QS (only 1 significant strong correlation). For EMG measures, the mobility walking task offering the highest number of significant strong correlations is QS (5 significant strong correlations), followed by HS (4 significant strong correlations), SS and FC (2 significant strong correlations), and then LS (only 1 significant strong correlation).

This study is limited to the lack of open-source datasets with sensor-based measures from stroke survivors [18]. EMG measures are limited to frequency domain features from rectified EMG timing curves. Although rectified EMG is a better predictor of the components of motor unit synchronization than the corresponding unrectified EMG at low contraction strengths [32], it was not possible to benchmark it with the correlations for unrectified EMG and neither time-frequency features that require smaller computational costs [31]. Future research should move towards recording and publishing datasets comprising physiological measures such as raw EMG and spatiotemporal measures from stroke population to increase comprehension of their needs.

5 Conclusions

This work showed that sensor-based spatiotemporal and EMG measures during walking are statistically significant strongly correlated with FMA-LE clinical scores. Step length, stride time, and cadence spatiotemporal measures were strongly correlated with the clinical scores during any mobility walking task, presenting higher correlations with FMA-LE than EMG measures. In fact, EMG measures from the tibialis anterior, rectus femoris, and medial hamstring were not strongly correlated with

FMA-LE scores during any task. However, PKF measure of gluteus medius, lateral hamstring, and vastus medialis muscles revealed strong correlations in multiple tasks. Moreover, the most appropriate walking task to collect multiple clinical meaningful spatiotemporal and EMG measures are LS and QS, respectively. These findings are promising to enable the use of spatiotemporal and EMG measures in clinical practice to support clinical diagnosis and treatment prescription and the future development of artificial intelligence methods to estimate the FMA-LE clinical scores.

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