A Microsoft Kinect-Based Point-of-Care Gait Assessment Framework for Multiple Sclerosis Patients

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***Abstract*—Gait impairment is a prevalent and important difficulty for patients with multiple sclerosis (MS), a common neurological disorder. An easy to use tool to objectively evaluate gait in MS patients in a clinical setting can assist clinicians to perform an objective assessment. The overall objective of this study is to develop a framework to quantify gait abnormalities in MS patients using the Microsoft Kinect for the Windows sensor; an inexpensive, easy to use, portable camera. Specifically, we aim to evaluate its feasibility for utilization in a clinical setting, assess its reliability, evaluate the validity of gait indices obtained, and evaluate a novel set of gait indices based on the concept of dynamic time warping. In this study, ten ambulatory MS patients, and ten age and sex-matched normal controls were studied at one session in a clinical setting with gait assessment using a Kinect camera. The expanded disability status scale (EDSS) clinical ambulation score was calculated for the MS subjects, and patients completed the Multiple Sclerosis walking scale (MSWS). Based on this study, we established the potential feasibility of using a Microsoft Kinect camera in a clinical setting. Seven out of the eight gait indices obtained using the proposed method were reliable with intraclass correlation coefficients ranging from 0.61 to 0.99. All eight MS gait indices were significantly different from those of the controls (*p*-values less than 0.05). Finally, seven out of the eight MS gait indices were correlated with the objective and subjective gait measures (Pearson's correlation coefficients greater than 0.40). This study shows that the Kinect camera is an easy to use tool to assess gait in MS patients in a clinical setting.**

***Index Terms*—Gait assessment, Microsoft Kinect camera, multiple sclerosis (MS).**

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I. Introduction

GAIT analysis of patients with neurological disorders, including multiple sclerosis (MS), is important for rehabilitation and treatment. In a clinical setting, gait analysis performed by physicians or therapists involves observing a patient's gait and documenting subjective assessments. Different clinical scores are proposed in order to quantify the level of disability in MS patients; among them the expanded disability status scale (EDSS), the self-scored MS walking scale (MSWS), the MS severity score, and the MS functional composite, which are widely used in clinical practice [1]–[4]. The EDSS is an ordinal clinical rating system ranging from 0 (no neurological disorder) to 10 (death due to MS) with the possibility of half unit increments. This clinical measure quantifies the patient's disability level in eight functional systems. Usually, patients with scores greater than five are unable to walk without an assistive device. It should be noted that the clinical ambulation score, which is one of the required scores for computing the final EDSS score, is determined by a clinician through clinical observation of a patient's gait. The clinical ambulation score appears to be more meaningful for the patient gait abnormality assessment as compared to the EDSS score, which also includes other factors in assessing disability, especially for EDSS < 5.5.

The EDSS clinical ambulation score can range from 0 to 12, however subjects with scores of 10 or greater are primarily wheelchair bound. On the other hand, MSWS is a 12-item, patient-rated walking measure, ranging from 0 to 100. Higher MSWS scores indicate that the patient's walking ability is more affected by the MS disease process. Both of these clinical measures are unable to detect subtle changes in a subject's gait due to disease severity or treatment response. A more systematic gait analysis can be carried out in a gait laboratory using motion capture systems, force plates, and electromyography sensors. However, the required setup involves elaborate preparation and marker placement, is expensive, and thus, renders it unsuitable for use as a point-of-care technology.

A number of indices based on time or distance characteristics of the human gait cycle have been proposed for objective gait assessment in neurological patients with gait abnormality. Specifically, studies have shown that a shorter stride length and gait swing time as well as a higher double support percentage in a gait cycle (i.e., the fraction of the time in a gait cycle where the two feet are on the ground) are observed in neurological patients with gait abnormality [5]–[7]. In addition, the range of

the hip and knee angle is smaller in MS patients as compared to healthy individuals [8], [9]. Correlations between time–distance and joint angle indices and the EDSS score have been investigated as well in [6] and [7].

Angles of the lower extremity joints in an MS patient's gait have also been investigated. However, researchers have reported contradictory results. Specifically, reduced hip and knee flexion and ankle plantarflexion at heel strike (i.e., the point in the gait cycle when the foot reaches the ground), and hip and knee extension at toe-off (i.e., the point in the gait cycle where the foot is no longer in contact with the ground) are reported in [10], while increased hip and knee flexion and ankle plantarflexion at heel strike have also been observed in [9]. The analysis in these studies involves point-to-point comparisons between preselected peak points of the joint angles during a gait cycle.

Although accurate gait analysis for MS patients could provide valuable insight on a patient's condition and the severity of disease symptoms, an easy-to-use system that can encourage clinical adoption does not exist. Motion capture systems, which are mainly used for experimental data collection for gait analysis, are expensive. Furthermore, motion capture systems can only track a set of reflective markers mounted on certain anatomical landmarks of a patient's body, and hence, their use requires a time-consuming patient preparation process. Moreover, operator training for motion capture systems is necessary to ensure acceptable accuracy. Finally, these systems are not portable and require a dedicated space that makes them further impractical for clinical applications.

The Microsoft Kinect sensor, which was developed for motion recognition in gaming applications, is an ideal candidate for an inexpensive system providing the capability for human gait analysis. The Kinect sensor includes a color camera and a depth sensor, consisting of an infrared projector and camera, and provides full-body 3-D motion capture. The Kinect sensor has been used for various clinical and nonclinical applications. The authors in [11] use the Kinect sensor for pose identification. In [12], joint angles identified by the Kinect sensor are compared to the "gold standard" obtained by a marker-based motion capture system for healthy subjects, which showed reasonable accuracy for clinical applications.

The validity of the Kinect sensor for the assessment of postural control was also examined by comparing the results obtained by the Kinect with those from a marker-based motion capture system [13]. In addition, the accuracy of this sensor for movement measurement in people with neurological disease, such as Parkinson's disease, has been examined in [14]. However, a limited number of studies have been performed to investigate the feasibility of the Kinect sensor specifically for gait analysis of MS patients [15]–[17]. In [17], the short maximum speed walk test was measured with the Kinect system, and its correlation with the EDSS could be observed. Furthermore, using machine learning and image processing techniques, movements of MS patients were compared with healthy subjects to identify subgroups with similar movement patterns in [16]. The authors in [18] have developed a framework to distinguish MS patients from healthy subjects by analyzing a number of tasks such as finger-to-nose and finger-to-finger tests. In [19], postural control in MS patients was assessed using the Kinect camera.

In this research, we develop a framework to quantify gait abnormality of MS patients using a Kinect for Windows (version 1) camera for point of care testing. The overall objective is evaluating the feasibility as well as reliability and validity of such a framework in assessing gait parameters in MS patients. To this end, preliminary data are obtained to validate our tool in the assessment of gait parameters in MS patients by comparing patients with normal controls. We examine whether the previously introduced MS gait indices used for gait abnormality diagnosis can be acceptably captured using the inexpensive, easy-to-use, and portable Kinect camera.

In addition to the previously introduced gait indices, a novel set of MS gait indices based on the concept of dynamic time warping (DTW) [20] is also introduced. The newly introduced indices can characterize a patient's gait patterns as a whole (rather than considering isolated events in a gait cycle), and quantify a subject's gait "distance" from the healthy population. To further evaluate validity, the association of MS gait parameters including our novel gait indices with a subjective gait measure (the MSWS) and objective gait assessment (the EDSS clinical ambulation score) is also investigated. Finally, we evaluate the possibility of using the proposed novel set of indices in the identification of the severity of MS gait dysfunction. This paper contains studies on the feasibility of using the Kinect sensor and the proposed supplementary postprocess analyses for clinical gait assessment of MS patients and point-of-care testing. This study is the first to evaluate the Kinect camera framework for point-of-care MS gait assessment, which compares MS patients and normal controls, and aims to quantify MS gait abnormality.

II. Gait Analysis for MS Patients

A. Subjects

MS patients were recruited for the study from the MS Clinic of the Montreal Neurological Institute and Hospital, a tertiary care center. Age (± 5 years) and sex-matched normal controls without neurological disease and other conditions, which could significantly affect gait, were recruited from local volunteers (colleagues and friends of the research team). The Montreal Neurological Institute and Hospital Research Ethics Board provided approval for the study. All study subjects provided their informed consent to participate in the study.

Inclusion criteria for MS patients were 1) a diagnosis of MS [21], 2) EDSS score of 1–6.5, 3) relapse free for at least 30 days prior to study, 4) gait abnormality on clinical evaluation, 5) ability to ambulate independently (with assistive device(s) if necessary) for at least 10 m, and 6) age > 18 years. Exclusion criteria were 1) cognitive or psychiatric conditions, which could preclude compliance with informed consent, study procedures, or study requirements and 2) the presence of other significant neurological and/or medical disorders.

We studied 12 MS patients and 10 normal controls. Two of the 12 MS patients were excluded due to corrupted captured data. The final study population consisted of ten MS patients (nine females and one male) and ten age and sex-matched healthy normal controls.

B. Study Procedures

The study was completed in one visit for all subjects. MS patients first underwent a medical history and physical

TABLE I
CLINICAL CHARACTERISTICS OF MS SUBJECTS

Patient No.	Sex	Age	Ambulation Score	EDSS	MSWS	Height [cm]	Weight [kg]
P1	F	53	6	6	89.6	146	55
P2	F	41	0	2	25	170	86
P3	M	79	5	6	47.9	169	91
P4	F	69	1	3.5	60.4	150	81
P5	F	75	5	6	72.9	157	89
P6	F	60	6	6	81	170	79
P7	F	55	4	5.5	83.3	168	81
P8	F	70	9	6.5	97.9	178	81
P9	F	53	6	6	75	174	59
P10	F	55	1	3	45.8	161	51

TABLE II
CLINICAL CHARACTERISTICS OF HEALTHY CONTROL SUBJECTS

Control Subject No.	Sex	Age	Height [cm]	Weight [kg]
C1	F	53	160	81
C2	F	36	165	70
C3	M	80	185	135
C4	F	71	163	82
C5	F	72	159	50
C6	F	62	147	59
C7	F	57	170	63
C8	F	67	170	63
C9	F	50	168	69
C10	F	51	165	53

examination including a neurological examination with calculation of EDSS score with the physician investigator (DAT). The EDSS clinical ambulation score was calculated as part of the EDSS. MS patients completed the MSWS. All controls underwent a medical history with the physician investigator (DAT) to ensure that they did not have neurological or medical difficulties that could affect their gait.

Following medical evaluation, all study subjects underwent gait assessment with the Kinect camera in a clinical area. The MS subjects were studied in the clinic hallway just outside the examining room of the physician investigator (DAT) at the Montreal Neurological Institute and Hospital. All subjects were asked to walk in front of the Kinect camera for 5–10 trials in order to obtain a video sequence with the subject moving in front of the camera in a straight line and toward the camera. The reason for this decision is attributed to the fact that the accuracy of joint positions detected by the Kinect is the highest when a subject is viewed from the front. The best five captures were selected for subsequent analysis (with the exception of the first patient for whom only three trials were available).

For each trial, the subjects were asked to walk at their normal pace. They were instructed to start their gait outside of the camera's field of view in order to ensure that their usual walking pattern had been established once they reached the capture zone. As the Kinect field of view is limited, depending on the stride length of the subjects, one or multiple gait cycles may have been captured. Most MS patients used an assistive device for ambulation. If this was the case, they were asked to use their usual assistive device, which included a cane, orthosis, or rollator walker. More specifically, five patients used a cane, one used a rollator walker, three used knee ankle foot orthoses (of these, one used bilateral knee ankle foot orthoses), and two used ankle foot orthoses for ambulation. The stored information related to each subject was deidentified to ensure patient confidentiality. The MS patient clinical information is summarized in Table I, whereas Table II summarizes clinical information for the healthy control subjects.

C. Data Analysis of Gait Variables

The Kinect for the Windows sensor with the use of its software development kit provides 3-D skeletal data on 20 joint positions over time. For the lower extremity, these joints consist of hip, knee, and ankle for each leg. The Kinect captures the video up to 30 frames per second. Joint positions are expressed in an inertial reference frame in which the y-axis is in the direction

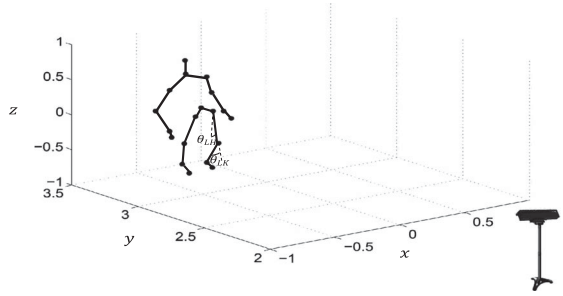

Fig. 1. Captured data and the identified joints using Microsoft Kinect. The left hip angle θ_{LH} and left knee angle θ_{LK} are shown in the figure as well.

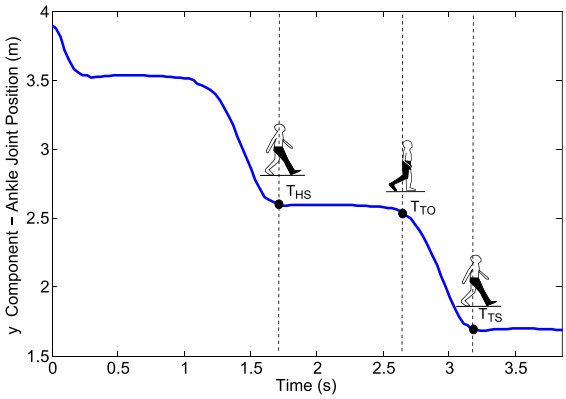

Fig. 2. Ankle joint position variation captured for Patient 6 (Trial 5). Heel strike, toe-off, and terminal swing phases are denoted by T_{HS}, T_{TO}, and T_{TS}, respectively.

of the runway, the z-axis is perpendicular to the ground, and the x-axis is mutually perpendicular to both (see Fig. 1).

The subject's kinematic properties can be extracted using the value of the joint positions. Joint angles, and if required, angular velocities and accelerations can be calculated based on the time history of the joint positions. The first step in the process involves identifying a complete gait cycle in the captured data. This can be accomplished by considering ankle position variations over time. A gait cycle starts with heel strike, implying that the ankle joint position is stationary (see T_{HS} in Fig. 2). At toe-off, the leg starts to swing, and hence, the ankle position starts to change (see T_{TO} in Fig. 2). Finally, the gait cycle terminates by the terminal swing in which the ankle position comes to rest again (see T_{TS} in Fig. 2). The ankle joint position variation for a representative subject is shown in Fig. 2.

In order to distinguish an abnormal gait from normal, and potentially quantify its degree of abnormality, appropriate gait indices need to be defined. Three categories of indices are defined for gait analysis in this study; namely, the time–distance indices and the joint angles (which have been discussed in the literature), and the gait-pattern-related indices, which are introduced in this paper. Here, four time–distance indices, namely, subject velocity, stride length, percentage double support time, and stride width are considered as suggested by the authors in [5] and [6]. In the joint angle category, hip and knee range of motion is considered due to the fact that studies show that MS can substantially affect these joints [8]. Finally, a novel index, which can capture the general gait pattern of the subject and its deviation from a healthy gait, is introduced.

A subject's velocity for one gait cycle can be calculated by dividing the stride length to the gait cycle time (from T_{HS} to T_{TS}). To be able to meaningfully compare distance indices, they are normalized based on a subject's height to compute normalized velocity V_n. Furthermore, normalized stride length L, defined as the distance travelled by the ankle in one gait cycle (i.e., between the heel strike T_{HS} and the terminal swing phases T_{TS}), stride width W, defined as the distance between the two ankles in the double support phase projected on the x-axis, and double support time percentage S, defined as the ratio of the stance time to the gait cycle time, can be calculated. Finally, the knee and hip angles need to be computed using the location of the joints. The knee angle is defined as the angle between the thigh and the leg segments, and the hip angle is defined as the angle between the z-axis and the thigh segment (see Fig. 1).

D. DTW

Although minimum and maximum joint angle values, range of motion, and time–distance indices can provide valuable information on a subject's gait characteristics, they only provide a snapshot at a specific time instant. Developing a framework capable of analyzing a complete gait cycle (as opposed to analyzing certain points in a gait cycle) provides a holistic approach for gait analysis and can complement the information provided by other indices. This involves developing a distance metric to quantify the level of abnormality of a gait cycle with respect to healthy individuals. There have been prior attempts in comparing MS gait patterns with control subjects by point-to-point comparisons at certain gait phases such as heel strike or toe-off [9], [10]. However, no study has introduced a mechanism to compare complete gait cycles.

Here, we propose a set of novel MS gait indices based on the DTW framework. DTW, which was initially proposed for speech recognition applications [22], provides a framework for finding an optimal alignment between two time series that have different time scales. This is ideal for comparing sequences representing the human gait cycle as any gait cycle includes the same gait phases (i.e., heel strike, toe-off, etc.); however, the transition time between these phases varies from subject to subject. DTW has been previously used in other nonclinical contexts such as human motion recognition and in identifying different modes of movements and motion patterns [23], [24]. DTW defines a cost function and uses a nonlinear transformation to warp the two sequences in order to minimize a cost function. The optimal value of the cost function can be regarded as a "distance measure" between the two sequences.

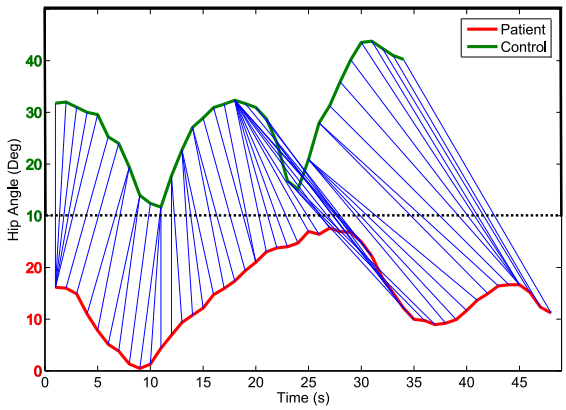

Fig. 3. DTW on the hip angle variations for an MS patient and a healthy control subject.

Consider the two sequences $\mathbf{A} = \{a_1, a_2, \ldots, a_N\}$, $a_n \in \mathbb{R}$, $n = 1, \ldots, N$ and $\mathbf{B} = \{b_1, b_2, \ldots, b_M\}$, $b_m \in \mathbb{R}$, $m = 1, \ldots, M$. A *local distance cost* between two elements of the sequence $a_n \in \mathbf{A}$ and $b_m \in \mathbf{B}$ is a mapping $c : A \times B \rightarrow \overline{\mathbb{R}}_+$ such that $c(a_n, b_m)$ increases as the mismatch between a_n and b_m increases. Next, define the cost matrix $\mathbf{C} = [c_{\mathrm{nm}}] \in \mathbf{R}^{N \times M}$, where $c_{\mathrm{nm}} = c(a_n, b_m)$, $n = 1, \ldots, N$, and $m = 1, \ldots, M$. A sequence $p = \{p_1, p_2, \ldots, p_L\}$, where $p_l = (n_l, m_l)$, $l = 1, \ldots, L$, $n_l \in \{1, \ldots, N\}$, and $m_l \in \{1, \ldots, M\}$, is referred to as a *warping path* if it satisfies the boundary, monotonicity, and step size conditions discussed in [20]. A warping path defines the point-to-point correspondence between the two sequences. The *total cost* $c_p(\mathbf{A}, \mathbf{B})$ for the two sequences $\mathbf{A}$ and $\mathbf{B}$ along a warping path p is defined as

$$c_p(\mathbf{A}, \mathbf{B}) := \sum_{l=1}^{L} c(a_{n_l}, b_{m_l}), \quad a_{n_l}, b_{m_l} \in p. \tag{1}$$

Finally, the *DTW distance* between $\mathbf{A}$ and $\mathbf{B}$ is defined as

$$\mathrm{DTW}(\mathbf{A}, \mathbf{B}) := c_{p^*}(\mathbf{A}, \mathbf{B}) \tag{2}$$

where $p^* := \mathrm{argmin}_{p \in \mathbf{P}} c_p(\mathbf{A}, \mathbf{B})$ is the *optimal warping path*.

E. DTW for Gait Analysis

Next, we present a framework that uses DTW to quantify severity of MS disease symptoms. Specifically, we investigate the association between DTW distance and the two clinical scores, namely, MSWS and EDSS clinical ambulation score.

The DTW framework can be used to align two sequences of different length (e.g., unaligned hip angle variations over time for a patient and a normal subject gait). Fig. 3 shows the two sequences for a representative patient and a control subject. The value of the DTW distance defined in (2) shows the deviation of a patient's joint pattern from a normal subject. A larger DTW indicates a larger deviation between patient and the healthy subject gait patterns, and potentially a more advanced stage of MS. In longitudinal studies, these novel DTW distances could potentially identify severity of MS disease symptoms in a particular patient over time and provide insight on a patient's response to treatments.

In this research, in order to evaluate a patient's gait, we extract time series for hip and knee angles for a complete gait cycle and compute the hip and knee DTW distances with respect to a set

of control subjects. Note that maximum hip and knee flexion angles are reported to be different in MS patients compared to healthy control subjects [9], [10]. In this study, the goal is to further investigate the relationship between the degree of gait abnormality and lower extremity joint variations over a complete gait cycle and not limit the analysis to extreme joint angles.

The dataset included in this study is composed of gait data collected from n_p patients, where each patient completed m_p trials. In addition, the control dataset is composed of gait data collected from n_c control subjects, where each control subject completed m_c trials. As discussed earlier, for each trial, one complete gait cycle from heel strike to toe-off is identified and the rest is discarded. Therefore, the overall dataset includes $n_p m_p$ gait cycles corresponding to MS patients and $n_c m_c$ gait cycles corresponding to healthy control subjects. For our study, $n_p = n_c = 10$ and $m_p = m_c = 5$.

For each patient, hip joint angles for the left and right legs over the entire gait cycle are calculated and stored in arrays $\theta_{\mathrm{LH}_{i,j}}$, $\theta_{\mathrm{RH}_{i,j}}$, respectively, where $i \in \{1, \ldots, n_p\}$ and $j \in \{1, \ldots, m_p\}$. Similarly, knee joint angles for the patient's left and right legs are stored as $\theta_{\mathrm{LK}_{i,j}}$, $\theta_{\mathrm{RK}_{i,j}}$, respectively, where $i \in \{1, \ldots, n_p\}$ and $j \in \{1, \ldots, m_p\}$. For control subjects, hip and knee joint angles for the left and right legs are calculated and stored in $\phi_{\mathrm{LH}_{q,r}}$, $\phi_{\mathrm{RH}_{q,r}}$, $\phi_{\mathrm{LK}_{q,r}}$, and $\phi_{\mathrm{RK}_{q,r}}$, respectively, where $q \in \{1, \ldots, n_c\}$ and $r \in \{1, \ldots, m_c\}$.

Here, we introduce a gait index referred to as the *mean DTW distance*. This index quantifies the degree of dissimilarity between a patient's joint angle pattern compared to a set of control subjects. Specifically, the DTW distance between two time series, namely, a patient's joint angle for a given trial and a set of control subjects' joint angles for all available trials are computed. Note that these distances are computed for the left and right legs independently. That is, a patient's left (respectively, right) leg joint angle sequence is compared with all left (respectively, right) joint angle sequences for all control subjects. Hence, overall $n_c m_c$ DTW distances are computed for each leg (in our case $n_c m_c = 50$). Considering the fact that m_p trials are available for each patient, $m_p n_c m_c = 250$ DTW distances are obtained for each patient's leg and each joint. Hence, a total of $2 m_p n_c m_p = 500$ DTW distances are computed for each joint (i.e., knee and hip). These distances are then averaged to compute the mean DTW distance associated with the knee or hip joint for each patient. Specifically, for Patient $i, i = \{1, \ldots, n_p\}$, the mean DTW distance for knee and hip joints, denoted by D_{K_P} and D_{H_P}, respectively, are defined as

$$D_{K_P} := \frac{1}{2}\left[\frac{1}{m_p n_c m_c}\sum_{j=1}^{m_p}\sum_{q=1}^{n_c}\sum_{r=1}^{m_c}\mathrm{DTW}(\theta_{\mathrm{LK}_{i,j}}, \phi_{\mathrm{LK}_{q,r}}) + \frac{1}{m_p n_c m_c}\sum_{j=1}^{m_p}\sum_{q=1}^{n_c}\sum_{r=1}^{m_c}\mathrm{DTW}(\theta_{\mathrm{RK}_{i,j}}, \phi_{\mathrm{RK}_{q,r}})\right] \quad (3)$$

$$D_{H_P} := \frac{1}{2}\left[\frac{1}{m_p n_c m_c}\sum_{j=1}^{m_p}\sum_{q=1}^{n_c}\sum_{r=1}^{m_c}\mathrm{DTW}(\theta_{\mathrm{LH}_{i,j}}, \phi_{\mathrm{LH}_{q,r}}) + \frac{1}{m_p n_c m_c}\sum_{j=1}^{m_p}\sum_{q=1}^{n_c}\sum_{r=1}^{m_c}\mathrm{DTW}(\theta_{\mathrm{RH}_{i,j}}, \phi_{\mathrm{RH}_{q,r}})\right]. \quad (4)$$

TABLE III
GAIT INDICES FOR MS PATIENTS

Index	Symbol	Unit	Description
Normalized velocity	V_n	s^{-1}	Velocity normalized by height
Normalized stride length	L_n	Unitless	Stride length normalized by height
Stance percentage	S	Unitless	Stance time divided by gait cycle time
Step width	W	m	Distance between the two ankles in double support phase projected on the x-axis
Hip range of motion	α_H	deg	Difference between minimum and maximum of the hip angle
Knee range of motion	α_K	deg	Difference between minimum and maximum of the knee angle
Mean dynamic time warping distance for knee	D_K	deg	See (3)
Mean dynamic time warping distance for hip	D_H	deg	See (4)

TABLE IV
STATISTICS FOR TIME-DISTANCE-DERIVED INDICES

	V_n [s^{-1}]	L_n	S [%]	W [m]
MS Mean (SD)	0.4 (0.14)	0.6 (0.1)	0.6 (0.05)	0.8 (0.2)
Control Mean (SD)	1.2 (0.14)	0.8 (0.07)	0.5 (0.03)	0.6 (0.18)
MS ICC	0.99	0.93	0.71	0.50
(95% CI)	(0.984, 0.998)	(0.83, 98)	(0.25, 0.92)	(0.63, 0.96)
Control ICC	0.93	0.90	0.75	0.80
(95% CI)	(0.84, 0.98)	(0.76, 0.97)	(0.38, 0.93)	(0.52, 0.95)
Correlation with Ambulation Score	−0.69	0.54	−0.14	0.43
(95% CI)	(−0.81,−0.50)	(0.30, 0.71)	(−0.40,0.15)	(0.17, 0.64)
Correlation with MSWS	−0.86	0.69	0.04	0.51
(95% CI)	(−0.91,−0.76)	(0.50, 81)	(-0.24, 0.33)	(0.26, 0.70)
t-test p-value	10^{-6}	10^{-4}	10^{-4}	0.044

Similarly, the mean DTW distance associated with the knee and hip joints for control subjects denoted by D_{K_C} and D_{H_C}, respectively, can be defined, where the distance between joint sequences for a control subject is compared with all other control subjects.

III. RESULTS

A. Analysis of Reliability and Validity of Gait Indices From Kinect

Time–distance and joint angle indices discussed in previous literature, and the novel mean DTW distance indices (proposed in this research) are computed for ten patients and ten age and sex-matched control subjects. A list with descriptions of all the computed indices is given in Table III.

For each data capture from a subject, the selected eight gait indices given in Table III are computed. First, the reliability of each index using the intraclass correlation coefficient (ICC) is evaluated. Specifically, the ICC is calculated for both patient and control groups. The results are provided in Tables IV and V. All gait indices are reliable with the exception of the step width in MS patients. In addition, knee range of motion in patients had a large confidence interval. Next, mean values for each index (averaged over five trials) for patients and control subjects are summarized in Tables VI and VII, respectively.

TABLE V
STATISTICS FOR ANGLE-DERIVED INDICES

	α_K [deg]	α_H [deg]	D_K [deg]	D_H [deg]
MS Mean (SD)	36 (5)	23 (3)	236 (68)	210 (47)
Control Mean (SD)	47 (9)	30 (4)	191 (54)	156 (36)
MS ICC	0.61	0.92	0.88	0.78
(95% CI)	(−0.01, 0.90)	(0.80, 0.98)	(0.69, 0.97)	(0.43, 0.94)
Control ICC	0.89	0.98	0.93	0.82
(95% CI)	(0.74, 0.97)	(0.94, 0.99)	(0.82, 0.97)	(0.54, 0.94)
Correlation with Ambulation Score	−0.42	−0.63	0.66	0.66
(95% CI)	(−0.64, −0.14)	(−0.78,−0.41)	(0.44, 0.80)	(0.45, 0.80)
Correlation with MSWS	−0.50	−0.42	0.64	0.62
(95% CI)	(−0.70,−0.24)	(−0.64,−0.14)	(0.41, 0.79)	(0.39, 0.77)
t-test p-value	0.0229	0.0067	0.0142	0.0026

TABLE VI
GAIT INDEX VALUES FOR MS PATIENTS

Patient	V_n [s^{-1}]	L_n	S [%]	W [m]	α_K [deg]	α_H [deg]	D_K [deg]	D_H [deg]
P1	0.34	0.44	66	0.68	36.7	18.2	167	175
P2	0.70	0.78	59	0.61	44.2	24.7	192	175
P3	0.48	0.67	58	0.59	34.8	22.0	195	210
P4	0.32	0.51	63	0.81	32.6	23.9	248	212
P5	0.41	0.58	61	0.84	31.2	22.9	271	244
P6	0.29	0.55	69	1.04	27.0	20.8	279	194
P7	0.43	0.67	58	1.02	33.7	27.8	230	236
P8	0.22	0.47	52	1.10	36.6	17.9	377	303
P9	0.33	0.59	54	0.83	44.3	43.9	463	358
P10	0.54	0.63	59	0.42	43.9	25.7	162	145

TABLE VII
GAIT INDEX VALUES FOR CONTROL SUBJECTS

Control	V_n [s^{-1}]	L_n	S [%]	W [m]	α_K [deg]	α_H [deg]	D_K [deg]	D_H [deg]
C1	1.35	0.78	45	0.64	43.1	19.8	168	160
C2	1.12	0.78	52	0.54	50.6	33.0	168	135
C3	1.12	0.73	53	0.95	33.6	24.7	201	165
C4	0.97	0.66	53	0.79	37.7	25.6	319	245
C5	1.38	0.90	48	0.41	48.4	33.2	165	132
C6	1.25	0.81	49	0.65	41.9	25.9	148	130
C7	1.19	0.80	48	0.58	51.8	30.9	164	144
C8	1.21	0.84	46	0.50	46.6	31.0	152	128
C9	1.16	0.71	54	0.31	42.4	29.2	174	158
C10	1.42	0.77	54	0.62	65.9	37.1	230	165

The computed values for all the gait indices are illustrated in Figs. 4–6 in the form of box plots. The gait indices are compared between patients and controls with unpaired t-tests. The results show a statistically significant ($p < 0.05$) difference for all eight gait indices between patients and controls (see Tables IV and V). Finally, associations between gait indices and clinical ambulation scores as well as the self-scored MSWS scores are evaluated with Pearson's correlation coefficients (see Tables IV and V). All gait indices, with the exception of double support percentage of gait cycle, are correlated with objective and subjective gait measures (EDSS clinical ambulation scores and MSWS scores). The hip and knee positions for Patient 9 showed severe noise and artifact, and hence, this patient was excluded from the analysis for indices involving the hip and knee. This is one limitation

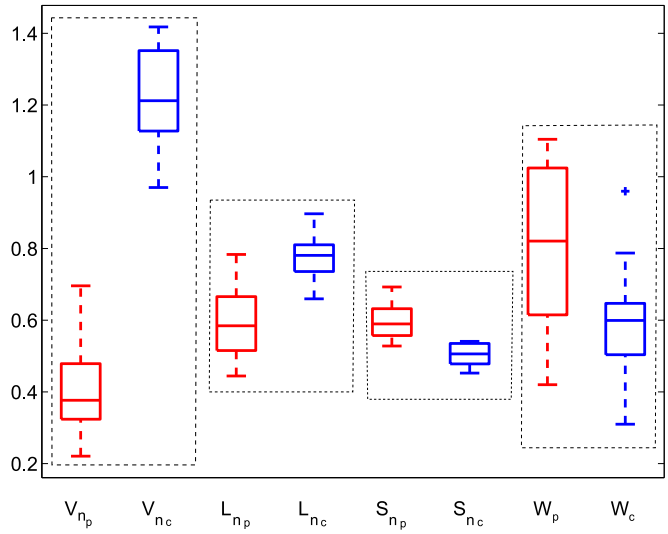

Fig. 4. Box plots for the time–distance-derived indices of the patients (red) and control subjects (blue), namely, normalized velocity V_n, normalized stride length L_n, Stance percentage S, and Stance width W.

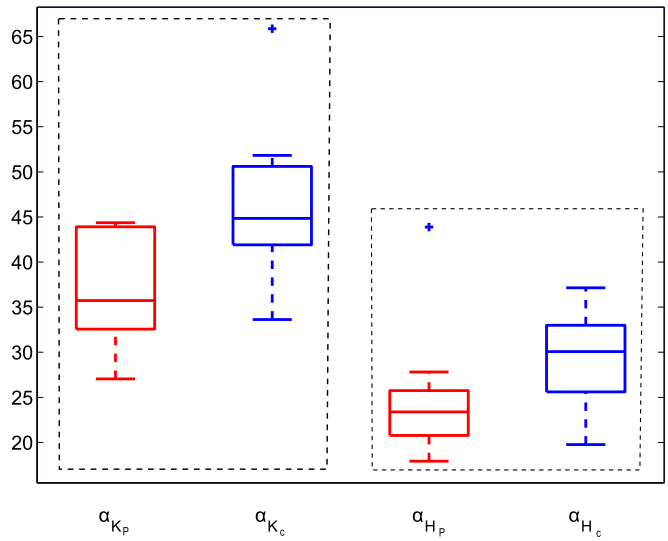

Fig. 5. Box plots for the knee and hip range of motion indices of the patients (red) and control subjects (blue), namely, α_K and α_H.

of the Kinect camera, where in a small number of cases some joints are not correctly identified. It is expected that the new version of the Kinect for Windows (version 2) will address this limitation.

B. Principal Component and Linear Discriminant Analyses of Gait Indices

Principal component analysis (PCA) is a powerful tool for multivariate statistical analysis [25]. This method generates a new set of variables (principal components) each of which are linear combinations of the original variables. Such a statistical transformation removes the redundancy in information. The accumulated variances of the first few principal components usually encompass the total variance of the original data. In addition, *linear discriminant analysis* (LDA) is another statistical tool, which can be used to classify (and quantify the separability

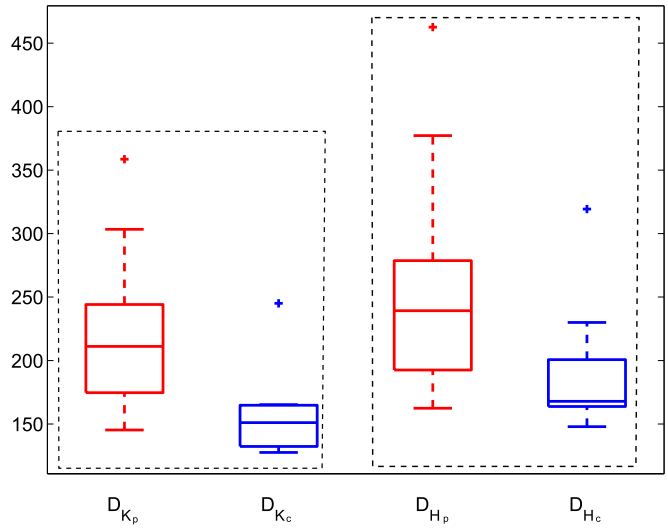

Fig. 6. Box plots for the knee and hip mean DTW distances of the patients (red) and control subjects (blue), namely, D_K and D_H.

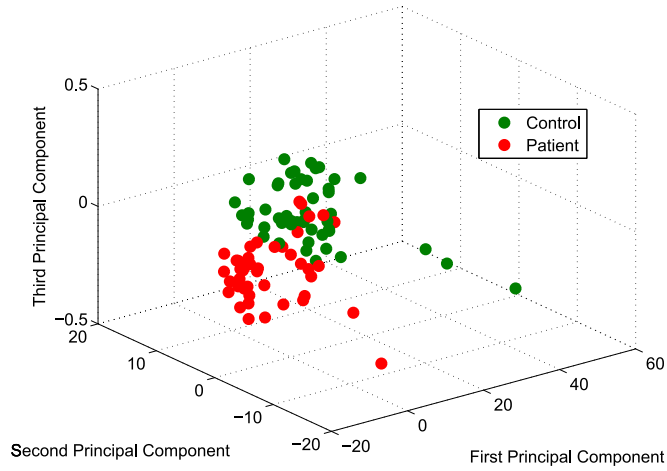

Fig. 7. First three principal components for the patient's and control's gait parameters associated with all the selected trials.

of) two or more groups of data [26]. LDA identifies a linear combination of the features in order to separate two or more classes.

Here, we use PCA to provide a 3-D graphical representation of the distribution of gait indices collected from MS and control subjects (see Fig. 7). Next, we use LDA to classify subjects into "MS" and "Control" classes based on gait indices derived from Kinect-generated data. Our goal is to show that gait indices derived from Kinect data can discriminate MS and control cases. However, note that this analysis does not establish the feasibility of using Kinect to detect MS (versus other neurological diseases). Rather, it provides preliminary results showing that clinical data indicate that gait indices derived from Kinect-generated data for MS and normal subjects are different.

Only time–distance and angle-derived indices, which show high correlations with the ambulation clinical score were included. These indices include normalized velocity, normalized stride length, and hip and knee range of motion. In order to test the performance of the LDA classification framework, we use a leave-one-subject-out cross-validation technique [27]. In

TABLE VIII
CONFUSION MATRIX FOR MS PATIENT AND CONTROL GROUPS

	MS Disease		
LDA Classification	Absent	Present	Totals
Normal	44	6	50
MS	8	40	48
Totals	52	46	98

TABLE IX
SENSITIVITY AND SPECIFICITY OF THE CONFUSION MATRIX FOR THE MS PATIENTS AND CONTROL GROUPS

		95% Confidence Interval	
	Estimated Value	Lower Limit	Upper Limit
Sensitivity	0.87	0.73	0.95
Specificity	0.85	0.71	0.93

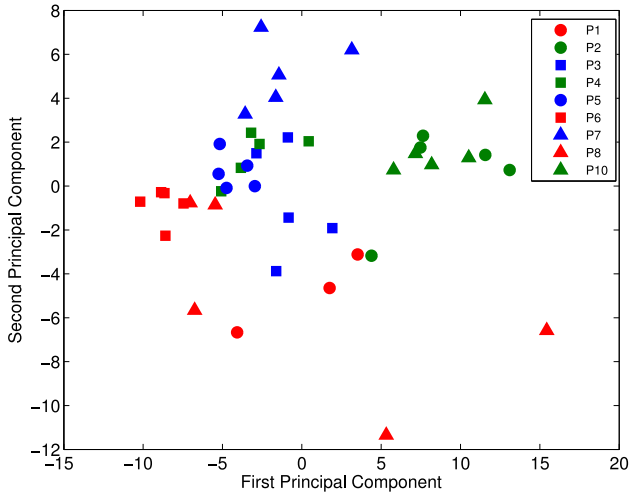

Fig. 8. First two principal components for the patient's gait parameters when the DTW distance indices are not considered. The green, blue, and red colors represent mild (ambulation scores less than 4), moderate (ambulation scores between 4 and 6), and severe (ambulation scores greater than 6) MS disease symptoms, respectively.

particular, the classifier is trained on all data collected from all subjects except for one, which is used to validate the algorithm. The process is repeated for all subjects. The results are summarized in a confusion matrix given in Table VIII. The sensitivity and specificity of the LDA classification framework, which can be used as a measure to quantify the performance of the classification algorithm, are given in Table IX.

Next, we illustrate the MS gait abnormality level among MS patients. Here, we exclude control subjects and PCA is applied only to indices collected from patients. The first two principal components capture the most significant directions in the data space. Projection of the gait indices onto the PCA space is shown in Fig. 8. Green, blue, and red colors represent subjects with mild (ambulation scores less than 4), moderate (ambulation scores between 4 and 6), and severe (ambulation scores greater than 6) levels of MS gait abnormality, respectively. The division of the patients into these three classes is based on clinical observation, where patients with ambulation scores less than 4 can usually walk at least 200 m without assistance (mild case),

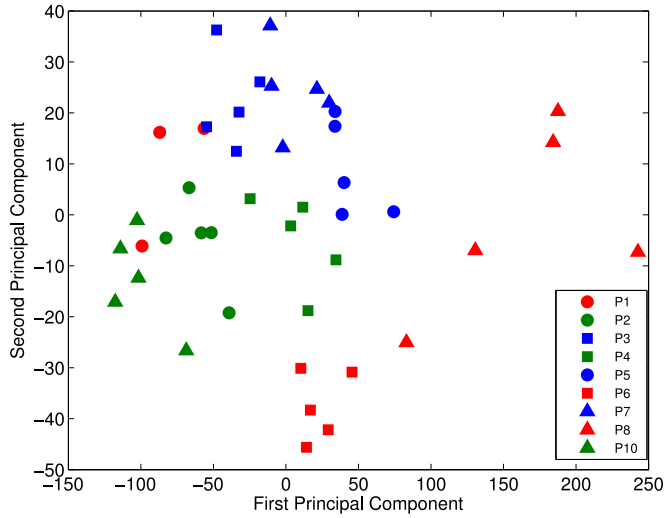

Fig. 9. First two principal components for the patient's gait parameters when the DTW distance indices are considered too. The green, blue, and red colors represent mild (ambulation scores less than 4), moderate (ambulation scores between 4 and 6), and severe (ambulation scores greater than 6) MS disease symptoms, respectively.

while those with the ambulation scores of greater than 6 need at least unilateral assistance (severe case). Finally, ambulation scores between 4 and 6 are referred to as moderate cases of MS in our analysis.

Finally, the hip and knee mean DTW distance indices, which contain information on the deviation of a patient's gait pattern from control subjects, are added to the previously selected gait indices and the first two principal components are selected (see Fig. 9). We notice that with the addition of DTW distance indices to the time–distance and angle-derived gait indices, the classes associated with mild, moderate, and severe gait abnormality are better separated. This result further demonstrates the potential advantage of the proposed mean DTW distance indices in quantifying the severity of MS disease symptoms.

IV. Discussion

Based on this study, the Kinect for the Windows camera is feasible to be used in a clinical setting in order to evaluate gait in MS patients. Moreover, seven out of the eight gait indices assessed using the Kinect-based system are reliable and valid. Specifically, the reliability of gait indices was evaluated with ICCs for both patients and controls. As shown in Tables IV and V, all gait indices have acceptable ICCs with the exception of step width in MS patients. Moreover, in the initial evaluation of validity, we observed a statistically significant difference between patient and control groups ($p \leq 0.05$). To further evaluate validity, the associations of the computed gait indices with objective and subjective gait measures are studied. All gait indices with the exception of double support percentage of gait cycle are correlated with the objective and subjective gait measures.

In this study, as the first step, the applicability of the Kinect camera in capturing the previously reported gait indices for the MS gait study is investigated. It was observed that the median velocity and median stride length are smaller for MS patients compared to healthy control subjects (see Fig. 4). Alternatively, the median of the double support percentage (computed by determining the percent of time in a gait cycle where both feet are on the ground and calculating the median over all the patients and control subjects) as well as the knee and hip range of motion are larger (see Figs. 4 and 5). These observations are in agreement with previously reported gait characteristics of MS patients [5]–[9]. Next, the importance of the newly introduced DTW indices for providing further insight on MS patients' gait pattern was investigated. Our study shows that the median hip and knee mean DTW distances increase significantly in MS subjects (see Fig. 6). Larger DTW distances imply that the patient's gait pattern in the MS population is not "similar" to the healthy control group.

PCA was performed to illustrate the discrimination of the MS patient group and the control group considering multiple computed gait indices. As shown in Fig. 7, the time–distance and angle-driven gait indices can separate patients from control subjects. However, adding the proposed DTW distance indices to PCA, the patient group can be further subgrouped into three levels of MS gait abnormality. It is important to note that PCA cannot appropriately illustrate the discrimination of different gait abnormality levels when only time–distance and angle-driven indices are considered (see Fig. 8), while such a distinction can be clearly made with the consideration of the DTW distance indices into the PCA (see Fig. 9). This result clearly demonstrates the strength of the proposed DTW distance indices when used in conjunction with the other gait indices to characterize MS patients' gait. Finally, a leave-one-subject-out cross-validation technique is used to measure the performance of LDA to classify MS and control subjects based on gait indices computed from Kinect-generated data. The sensitivity and specificity of the LDA classification algorithm is 0.87 and 0.85, respectively, which signifies an acceptable level of classification performance (see Tables VIII and IX).

A. Current Limitations and Future Work

We have validated our proposed framework on ten patients and ten sex and age-matched control subjects. Although our results are very promising, further studies involving larger populations of patients and healthy controls to duplicate our results and improve reliability would be useful. Furthermore, although the use of Kinect for gait analysis of healthy subjects has been previously validated in the literature by comparing the results with those obtained by marker-based motion capture systems (the "gold standard"), our study can be further improved by also validating our MS patient data with a marker-based capture system. In this study, we focused on the comparison between MS and normal controls, and evaluated the correlation between gait-related indices and a clinician-assessed subjective gait measure. A larger study, which includes gait analysis in a gait laboratory, needs to be considered as part of a future study.

Moreover, although this study, as well as a number of previous studies reported in the literature, has demonstrated that the accuracy of the Kinect camera can be adequate for this application, the system has a number of shortcomings that can be addressed in future versions of the camera and software de-

velopment toolkit. The captured ankle angle and position are generally not accurate, and hence, this joint was excluded in our gait analyses. This issue can be potentially addressed in the recently released version of Kinect (version 2), which provides higher accuracy for the captured motion. Also, the new version of the Kinect camera with higher accuracy can improve the quality of the captured data, and consequently, improve the reliability of our results. We excluded one patient (Patient 9) due to severe artifact as discussed earlier. Moreover, in order to further improve the accuracy of the captured data, better tracking methods can be implemented, which use the raw depth Kinect data instead of relying on the application programming interface provided by Microsoft. In future research, we will explore manifold learning techniques such as maximum variance unfolding [28] and t-SNE [29] for dimension reduction. In addition, we will use classification techniques including support vector machines [30] and neural networks to classify subjects into different classes corresponding to different levels of MS disease symptom severity.

Finally, due to Kinect's limited range of view, depending on the stride length of a subject, only one to three complete gait cycles can be captured. Hence, this poses a limitation on gait tests and experiments, which require multiple continuous gait cycles. We attempted to overcome this limitation by recording a subject's gait multiple times and considering five trials for further analysis.

In summary, this study establishes a framework to use the Kinect camera to objectively assess gait abnormality in MS patients in a clinical setting. Specifically, we used the Kinect camera to compute previously reported gait indices as well as novel DTW-based distance indices to quantify the MS disease ambulation progression level, which has not been addressed previously. The output information and corresponding conclusions via such an inexpensive, portable, and easy-to-use tool may also provide unique opportunities for remote monitoring of a patient's gait condition. Furthermore, the system can provide invaluable objective insight on severity of MS disease symptoms and response to treatment.

V. Conclusion

An easy to use framework was developed to objectively evaluate gait in MS patients. Such a framework can quantify gait abnormalities in MS patients using the Microsoft Kinect for Windows sensor; an inexpensive, easy to use, portable camera. The feasibility of the developed framework for utilization in a clinical setting and its reliability were investigated. Moreover, the validity of gait indices obtained with the developed framework, as well as a novel set of gait indices proposed based on the concept of DTW were evaluated. In this study, ten ambulatory MS patients and ten age and sex-matched normal controls were studied at one session in a clinical setting with gait assessment using a Kinect camera. The EDSS clinical ambulation score was calculated for MS subjects, and patients completed the MSWS. The captured MS gait indices were significantly different from those of controls and were correlated with the objective and subjective gait measures. PCA and LDA were also performed to distinguish the patient population from the control subjects, and quantify the level of progression of the MS disease in patients. The study showed that the Kinect camera is an easy to use tool to assess gait in MS patients in a clinical setting.

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