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6. New comprehensive methods for the biomechanical analysis of knee osteoarthritis

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Abstract. Although the pathogenesis of osteoarthritis (OA) results from a complex interplay of factors, there is a predominant role of mechanical features in the development and progression of knee OA. Biomechanical gait analysis providing quantitative information on the knee joint structure and motion is therefore important as it can offer new insights into evaluation of the OA knee joint during functional activities. This chapter will review the biomechanical data acquisition of OA patients during gait. The systems used to perform data acquisition in terms of motion, force, muscle activation and inertial capture will also be described, as well as the main results from the literature on how these biomechanical parameters are modified during OA. Finally, some techniques allowing for the classification of the findings from biochemical analyses of knee OA, which can be of great help in the disease diagnosis and treatment, will be presented.

Introduction

Osteoarthritis (OA) is the most common type of musculoskeletal disorder, and the knee is the most affected joint [1]. Although the

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pathogenesis of OA is complex, systemic factors as well as local mechanical factors are of prime importance [2, 3]. Systemic factors include age, sex and racial characteristics. Mechanical factors, although of key importance in the etiopathogenesis of OA, act in association with the systemic factors. Among the mechanical factors, muscle weakness, joint injury, and obesity [4] are leading factors that account for the development and progression of the disease. Knee OA is also strongly linked to weakness of the quadriceps muscles [1, 5].

When treating OA, clinicians aim to reduce pain and improve function. When this fails, surgery remains the last option. However, to counter this fate and as stated by Hunter [3], we need to "change this paradigm to intervene when structural changes may be reversible." This suggests that the focus should be on modifiable risk factors and to reassess, among other options, physiotherapeutic approaches. However, such approach needs to be properly considered using appropriate biomechanical assessment techniques.

In view of the major role of mechanical factors in the development and progression of knee OA, biomechanical gait analysis measuring mechanical loading during walking is important as it provides quantitative information about the structure and motion of the knee joint, which can offer new insights into its evaluation during functional activities. As a result, knee joint disease can be better identified, facilitating diagnosis and treatment.

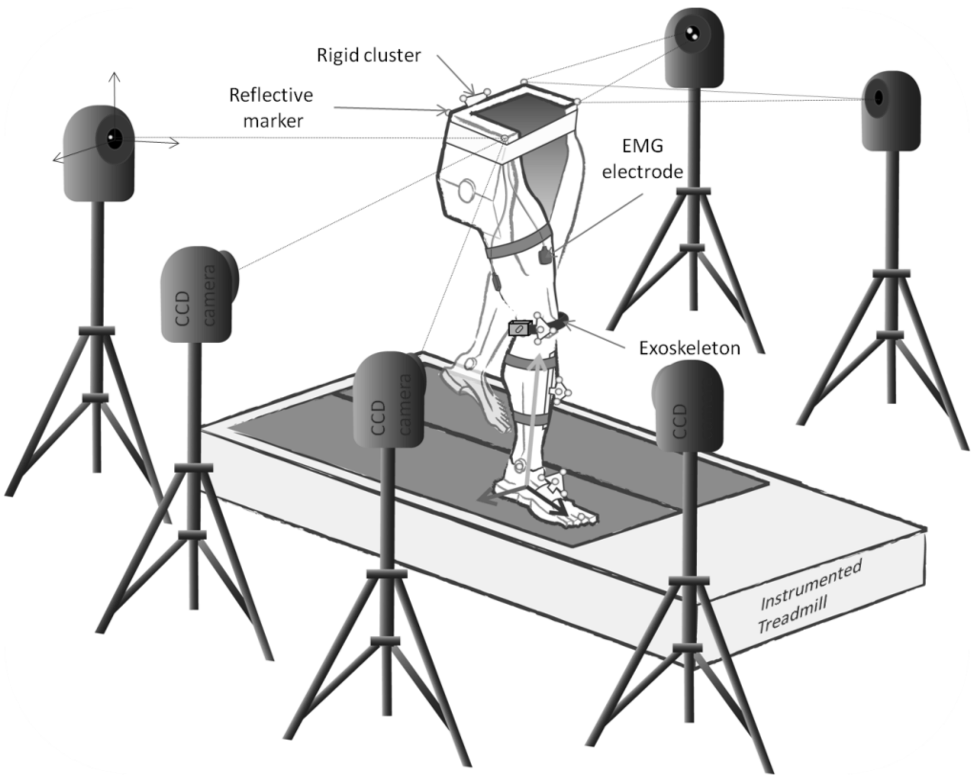

Figure 1. Gait analysis recording equipment setup (Imaging and Orthopaedics Laboratory, University of Montreal Hospital Centre, Montreal, Quebec, Canada).

Biomechanical data acquisition

This section reviews the biomechanical data acquisition equipment and methods. Figure 1 represents a typical gait analysis setup. In brief, a subject walks on a force platform that records the ground reaction forces (GRF). Generally, active or passive markers are fixed onto the human body segments and viewed by a motion capture system that records their three-dimensional (3D) trajectories. Kinematic data such as 3D knee joint angles are estimated from these trajectories. These data combined with GRF and inverse dynamic models are then used to calculate joint moments in all three anatomical planes. Additionally, surface electrodes positioned on the subject collect electrical activity for specific muscular groups.

Motion capture

Motion capture systems are generally composed of optoelectronic cameras which track 3D coordinates from active or passive markers that are placed over standardized anatomical landmarks to identify body segments. The markers can be either active (CODA, Charnwood Dynamics, Marseille, France; Optotrak, Northern Digital Inc., Waterloo, ON, Canada) or passive (also called reflective) (Vicon, Los Angeles, CA, USA; Motion Analysis, Santa Rosa, CA, USA) and are positioned in locations that represent the action of the underlying joint [6]. Passive systems send out infrared light signals and detect the reflection from the markers using multiple video cameras (minimum 3 but 6-8 cameras are often recommended). Active markers are light emitting diodes (LED) that are powered and cabled, and each LED sends a pulse sequence. The pulses are recorded by three non-collinear cameras (Optotrak, Northern Digital Inc.; VisualEye, Phoenix Technologies Inc., Burnaby, BC, Canada) mounted on a fixed base.

Both passive and active marker systems require markers to be attached to the subjects. There are two approaches for the positioning of markers on the limbs [7]. One approach is to place markers directly onto the skin, usually over a bony anatomical landmark. The other is to fix a set of at least three markers to each limb segment (rigid body), either directly or placed on a rigid structure. Both of these approaches allow representation of the motion of the body segment, but are subject to skin movement artefacts when movements out of the sagittal plane have to be assessed. Several non-invasive knee attachment systems have been validated for gait applications, and have shown to reduce skin motion artefacts [8, 9]. Figure 2 illustrates an example of such an attachment system (KneeKG, Emovi, Laval, QC, Canada).

Figure 2. Attachment system developed and validated by the Imaging and Orthopaedics Laboratory, University of Montreal Hospital Centre, Montreal, Quebec, Canada. Semi-circular rigid ring is affixed between medial and lateral femoral condyle and tracks the 3D displacement of the femoral segment, whereas a semi-rigid plastic sheet is fixed along the longitudinal tibial axis and tracks the tibial segment [8, 10, 11].

Force platforms

The general designation given to the forces that cause movement is kinetics. The latter includes both internal and external forces. External forces come from the ground or from external loads. As body weight drops onto and moves across the supporting foot, vertical, anterior-posterior and medial-lateral GRF are generated on the ground that can be measured with appropriate instrumentation [6]. The measurement of the GRF is performed using a force platform, which a patient walks across. It consists of a non-deformable steel plate with transducers at its corners to convert an applied load into electrical output signals. The two most widely used force platforms are the piezoelectric based transducers (e.g. from Kistler Instruments, Amherst, NY, USA) and the strain gauge-based platform (e.g., from AMTI Force and Motion, Watertown, MA, USA; Bertec Corporation, Columbus, OH, USA).

The force platforms are generally integrated into a walkway or an instrumented treadmill. The force platform positioned into a walkway below floor level provides a natural walking environment, but needs repetitive measurements in order to ensure the proper recording of a full stride. The treadmill is more convenient for gait analysis studies in a small area and allows control of several test conditions such as treadmill slope and speed. However, Riley et al. [10] reported that generally there is a subtle difference (i.e. an underestimate of two degrees) in the sagittal joint angular displacement between the treadmill and over ground gait data, but concluded that the magnitudes of these differences are all within the range of repeatability of measured kinematic parameters. Moreover, walking on the treadmill can initially be an unfamiliar experience, which in turn may influence the parameters being measured. Therefore, measurements have to be done after an adaptation time [11]. The GRF are frequently used in conjunction with numerical models and accurate joint centre location to compute the related rotator moments, centres of pressure and joint torques (moments at the joint).

Electromyography

Electromyography (EMG) is the analysis of the electrical activity of the contracting muscles. It is useful for detecting muscles that are or are not working, the on/off timing of the muscle activity, and the intensity or amplitude of the muscle electrical signals. EMG data acquisition is generally achieved using surface electrodes; however, the EMG recorded using skin surface sensors may not be very specific due to the interference from adjacent muscles. It can also be performed using fine wires inserted into the muscle of interest by hypodermic needles. The latter approach, although providing valuable local information regarding the targeted muscle activity, is invasive, uncomfortable, and can be painful.

Inertial systems

Inertial systems are composed of accelerometers, gyroscopes and magnetometers. Accelerometers are sensitive to the linear acceleration of the body, gyroscopes to the angular velocity of the body segment, and magnetometers to the direction of magnetic pole. The technology called MEMS (Micro Electro Mechanical Systems) helps to reduce the size and weight of these sensors in order to facilitate their use in human motion studies. In general, a fusion algorithm that combines all triaxial sensor information enables the determination of the relative orientations of the body limb segments [12, 13]. However, although being low cost and portable for data monitoring, the current MEMS gyroscope technology is prone to drift problems, i.e. the angular velocity of the rigid-body is continuously drifting at a very low rate and this is mainly due to the terrestrial movement. These phenomena could cause errors in the estimation of the rigid-body orientation for long monitoring periods.

Biomechanical characterization of knee OA

Spatiotemporal parameters

The gait cycle is defined as the period from the heel contact of one foot to the next heel contact of the same foot. It is common to start the cycle (0% of the period) with the first contact so that the end of the cycle (100% of the period) will be the initial contact of the next cycle. The gait cycle can be divided into two parts: the stance phase and the swing phase. The stance phase is the period of time during which one or two feet are in contact with the ground, and lasts approximately 60% of the gait cycle. The swing phase is the period when one foot is not in contact with the ground and lasts approximately 40% of the gait cycle. The stance phase can moreover be divided into three sub-phases, namely the ipsilateral double support, the ipsilateral single support and the final contralateral double support periods. The swing phase is also divided into three sub-phases: the initial swing, the mid-swing, and the terminal swing (Figure 3) [6].

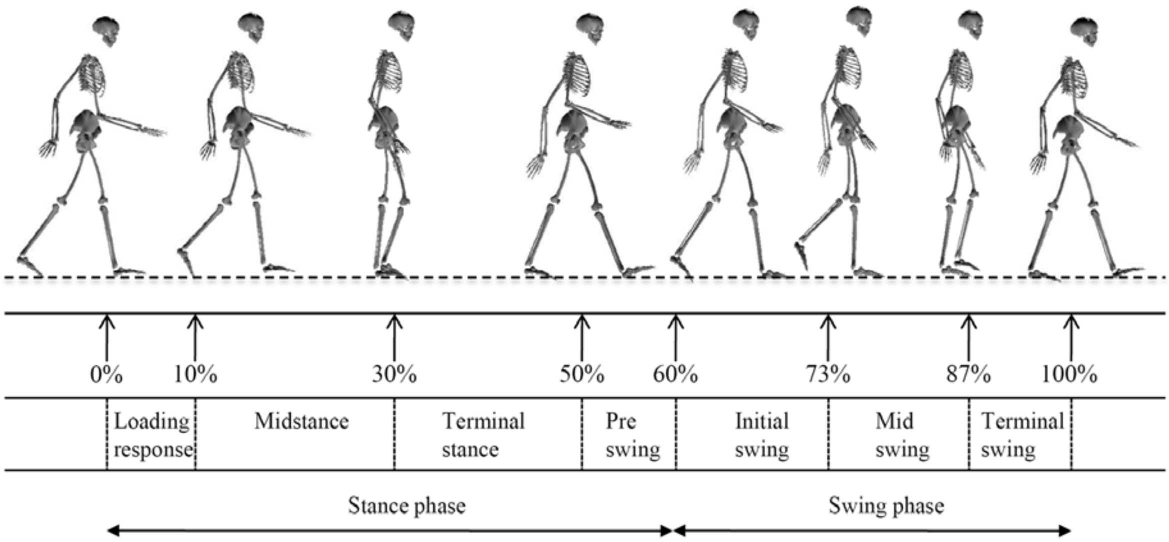

Figure 3. The gait cycle.

The general gait parameters, also known as spatiotemporal parameters, are the cycle time (or cadence), the stride length, and the walking speed (or walking velocity). The cadence may be measured by counting the number of individual steps taken during some known interval of time. Similarly, the walking speed can be measured by timing the subject during some known walking distance. The stride length can be determined directly by counting the number of strides during a walk of known distance, or indirectly by multiplying the speed by the cycle time. Spatiotemporal parameters are generally considered important in knee OA assessment.

Walking speed

Several studies have investigated whether patients with knee OA adopt a particular strategy regarding walking speed. Some studies determined that elderly patients had particularly lower walking speeds than the healthy control subjects of the same age group [14-20]. Furthermore, the gait speed tends to decrease with increasing Kellgren-Lawrence (KL) disease severity grade; i.e., patient groups with moderate OA (KL 3) and severe OA (KL 4) exhibited a significantly lower self-selected walking speed than the control group [17, 18]. Liikavainio et al. [21] investigated the effect of speed on the GRF at level walking for a group of elderly men with OA (KL 1-4) and a healthy matched control group. The most important findings of the former study [21] were that the differences in gait kinetics were minor in level walking at each predetermined gait speed in patients with knee OA compared with healthy age- and sex-matched control subjects. Moreover, no differences were reported in self-selected walking speeds between knee OA patients and healthy subjects [22-24].

Stride length and cadence

At a self-selected walking speed, knee OA subjects' cadence and stride length are shorter compared to asymptomatic subjects [14-16, 25, 26], and the stride time and double support period increase accordingly. The overall stance phase is longer for knee OA subjects [17, 18, 27]. At a constant fixed walking speed, moderate OA patients walked with stride characteristics similar to the control subjects [27, 28]. This implies that the changes in stride characteristics result partially from a reduced gait speed as part of the adaptive mechanism of knee OA patients [21]. A further analysis, which considers gender in the analysis of spatiotemporal parameters, shows that although the normalized gait speed, normalized step length, and cadence did not differ between males and females, the males had a significantly shorter stance and double support phase and a longer swing and single support phase than females [29].

Kinetic data

Vertical loading rate

Several studies have compared the GRF vertical component curves in knee OA patients and healthy subjects, leading to conflicting results as to the vertical loading rate (VLR), i.e. the slope of the GRF vertical component curve (Figure 4). Indeed, some studies reported that the VLR is higher in individuals with knee OA than in healthy control subjects [22, 30]. The increase, evaluated at 50%, occurs in conjunction with an increased intersegmental axial loading rate at all joints of the lower extremity [22]. However, others reported no difference between the VLR of hip or knee OA patients and those of healthy subjects during treadmill walking at a low speed [26]. Such differences between studies can be explained by the fact that the

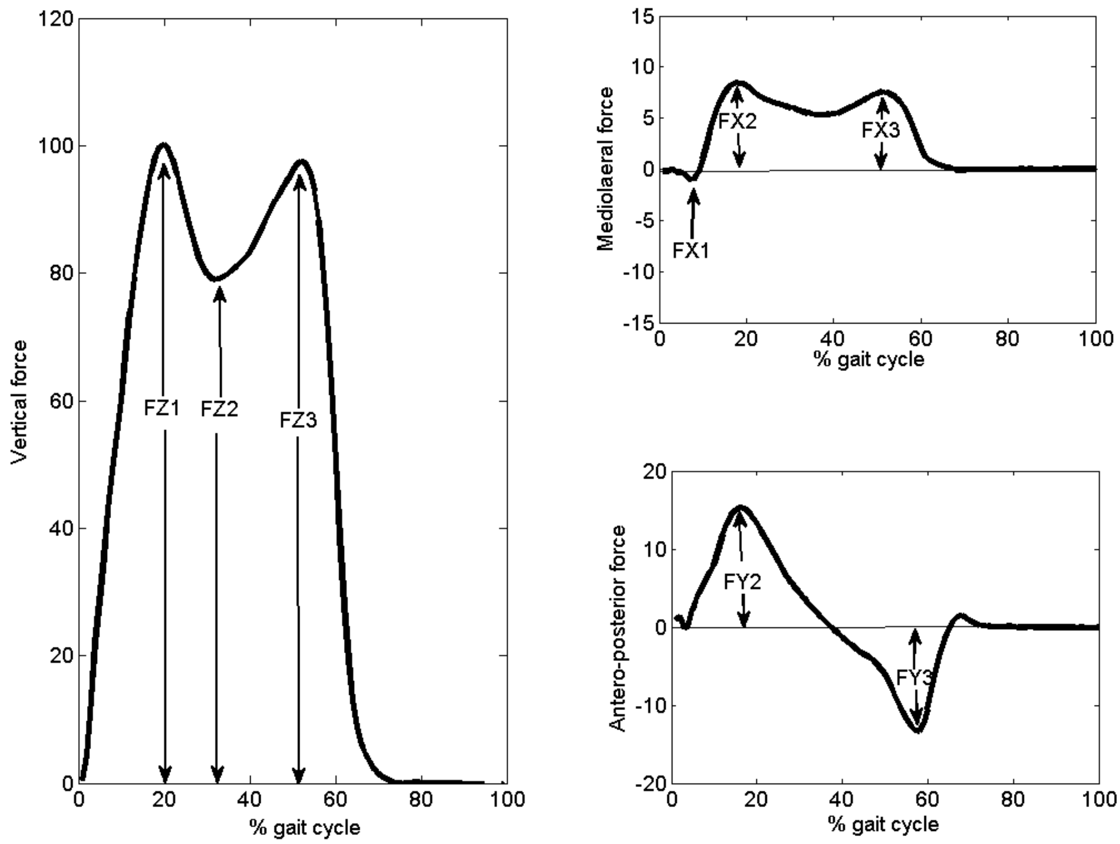

Figure 4. Biomechanical data. Left: vertical force. Right: medio-lateral force (upper panel) and antero-posterior force (lower panel). Vertical units are expressed in percentage of body weight.

gait protocols differ in terms of walking speed. Yet, other studies showed lower knee OA loading rate and vertical peak parameters [15, 31]; at a self-selected speed, significant reductions in the GRF vertical component variables have been noted when comparing subjects with moderate OA (KL 2–3) and severe OA (KL 4) to a control group [20].

Moments

The external adduction moment at the knee is the resulting moment creating a knee adduction during the stance phase of gait [25]. It represents the load distribution in the tibiofemoral compartment. Its effect is due to the fact that, in normal people, the line of action of the resulting GRF is oriented medially from the knee centre [32]. Miyazaki et al. [33] have shown in knee OA patients with a follow-up of 6 years that the external adduction moment was significantly correlated with a decrease in intraarticular space (r = 0,62; p<0,0001). They also showed that if the adduction moment increased by 1%, the risk of intraarticular space reduction increased 6-fold. The adduction moment could then be used as an indicator of disease progression. However, caution must be exercised when interpreting the increase of the adductor moment as an increase in OA severity since the former is related to the walking speed due to inverse dynamic modeling approach.

Impulsive loading and accelerometric data

Impulsive forces in the knee joint have been proposed to be a co-factor in the development and progression of knee OA. During normal walking, impulsive forces are created in the foot-ground interface at heel strike. These forces travel up the lower limb as a shock wave, also known as the heel strike transient [34]. Impulsive loading and shock absorption by the skeleton during gait have been studied using skin (SMA) and bone (BMA) mounted surface accelerometers. In an in vitro accelerometric study (i.e. BMA), Chu et al. [35] reported a reduction of 5% in load attenuation capacity in a degenerative knee compared to a healthy one. Hoshino and Wallace [36] investigated the impact absorbing properties of the knee joint during longitudinal impulsive loads and found a significant decrease in the absorbing capacity of a degenerative knee using BMA techniques. Radin et al. [37], using accelerometers fixed on the lateral side of the shank and the thigh (i.e SMA), showed a significant difference in longitudinal tibial and femoral accelerations between painful and asymptomatic knees at initial foot contact. However, SMA induces important artefacts during locomotion activities in comparison with BMA. In a pioneered exploratory investigation, Lafortune et al. [38] quantified the difference between the SMA and BMA techniques during a running task. They reported a substantial increase in magnitude of acceleration for SMA measurements compared to BMA at the tibial level. Although BMA techniques reduce skin movement artefacts, they are highly invasive for clinical use. Recently, Turcot et al. [39] developed an experimental numerical method of fixation of an accelerometer onto an exoskeleton which enables the transformation of the SMA measurements into estimated BMA measurements. This technique used inertial systems combined with a calibration technique as well as frontal X-ray of the knee to assess the linear acceleration of the internal tibial plateau as well as the internal femoral mid-condyle. Using this method, they reported [40] a statistically significant increase in linear acceleration of about 182%, 55%, and 163% in medial lateral internal tibial, medial lateral internal femoral, and anterior posterior internal femoral acceleration, respectively, for an elderly OA group (KL 3, 4) when compared to a matched healthy elderly group. This method has recently been used in therapeutic intervention, and its reliability and robustness was assessed in a repeatability study. Hence, in a controlled trial, data showed that therapeutic interventions (such as strengthening and proprioceptive exercises) had a beneficial effect of reducing the increase in femoral acceleration in the anterior posterior direction for the group with higher grade OA (KL 3, 4) [41]. This study demonstrated that the estimation of knee acceleration parameters is sensitive to changes in knee OA gait after rehabilitation. It also indicates that a three month treatment which combines strengthening and proprioceptive exercises could have beneficial effects on knee OA pain reduction by increasing anterior posterior knee stability and minimizing joint loading transmission during gait which reduces pain during walking [42].

Kinematic data

Kinematics of patients suffering from knee OA has been studied mostly in the sagittal plane [14, 15, 17, 25, 29, 43-45]. Investigators compared specific parameters of the gait cycle, such as knee angle at heel strike, maximum knee angle during loading, minimum knee angle at the end of the single support phase, maximum knee angle during the swing phase and range of motion during the gait cycle. The authors generally agree that OA patients walk with a reduced maximum flexion angle during the swing phase [14, 15, 17, 44] and reduced range of motion during the whole gait cycle [17, 25, 30].

Results on kinematics in the frontal and transverse plane are scarce. Tibial rotation has been studied only in a static position with ultrasound imagery [46] at 20^o of knee flexion. Nagao et al. [46] reported that OA patients tended to reduce internal rotation and that this effect increased with disease severity. Results obtained during a movement from 20^o to 5^o (similar to the unipodal phase during gait) led to the conclusion that "…osteoarthritis knee joint then moved more like a simple hinge joint" denoting that the screw-home mechanism was no longer present in these knees.

Some authors studied frontal plane kinematics. Indeed, varus/valgus malalignment, in addition to external adduction moment, has been recognized to predict OA progression [1, 47]. Varus/valgus malalignment is measured on a pangonogram (hip-knee-ankle film) as the angle between the longitudinal axis of the femur (aligning the centre of the femoral head with the centre of the knee) and the longitudinal axis of the tibia (aligning the centre of the knee with the centre of the ankle). Sharma et al. [48] studied knee OA progression and showed that a varus malalignment was associated with a 4-fold increase in the risk of joint space narrowing and correlated with pain. This study also showed that a malalignment greater than 5^o was related to a 3-fold increase in risk of functional impairment.

In 2004, Chang et al. [49] defined the varus thrust as the "visualized dynamic bowing-out of the knee laterally, i.e. the abrupt first appearance of varus (or the abrupt worsening of existing varus) while the limb is bearing weight during ambulation, with return to a less varus alignment during the non-weight-bearing (swing) phase of gait." These authors [49] performed a qualitative assessment of the varus thrust using a videotaping technique during level walking and data showed that varus thrust was present in 17% of cases. In a recent 3D kinematic study on OA patients with varying degrees of knee OA using an external attachment system (KneeKG, Emovi) allowing precise and repeatable measurement of knee kinematics in all three anatomical planes, an excellent correlation between mechanical knee alignment and abd/adduction movement during gait was found [50]. Moreover, this study also showed that frontal plane kinematics evolved with severity of the pathology towards adduction [51].

Electromyography

The electrical signal associated with the contraction of a muscle is called an electromyogram (EMG). Voluntary muscular activity results in an EMG that increases in magnitude with the tension [52]. Periarticular muscle weakness at the knee complex may also cause OA [53]. Although weakness in the quadriceps muscle is common in patients with knee OA [5], it has generally been considered a consequence of the pain that occurs with loading of the affected joint, leading the patient to minimize load bearing, in turn leading to disuse atrophy of the muscle [54]. However, the extent to which the muscle weakness in OA subjects may be associated with pain or indirectly with the effect of chronic pain disuse and muscle atrophy is not clear [55].

Given the role of muscles in influencing knee joint load and knee instability, an understanding of deficits in muscle function associated with knee OA becomes important. Three aspects of muscle deficits have been considered: muscular strength, muscle-activation patterns, and proprioception. In general, quadriceps strength is measured by the torque developed at the knee level and reported in Nm. However, strength also varies with body size and it should be reported in a normalized form as a percentage of body weight. Patients with knee OA are 20% to 40% weaker in relative quadriceps strength than healthy controls [56]. Muscle strength deficits are generally associated either with muscle fibre atrophy or inhibition of the ability to activate the muscle. Ikeda et al. [57] reported a 12% decrease in the cross-sectional area of the quadriceps in women with signs of OA compared to controls. Using surface EMG data from vastus lateralis and medialis, lateral and medial hamstring and gastrocnemius muscles, Hubley-Kozey et al. [58] analyzed three groups consisting of asymptomatic subjects and moderate and severe OA patients during gait analysis. They found a significant effect of pathology on four muscle co-activation patterns between these groups. They concluded that muscle co-activity provides additional information related to OA severity.

Knee joint proprioception is essential in the coordinated activity of surrounding muscles. It is generally measured by the sense of joint position. Deficits in proprioception have been found in knee OA subjects. However, the link between proprioception, physical function, and pain is still not clear [56]. There is some evidence that quadriceps weakness precedes the onset of knee OA and hence could increase the risk of disease development, particularly in women. Thus, quadriceps strengthening exercises may play a role in the earlier prevention of OA development in women. Turcot et al. [40] also showed that a three month treatment combining strengthening and proprioceptive exercises could be beneficial in knee OA pain reduction by increasing anterior posterior knee stability and stabilizing joint loading transmission during gait. In fact, the authors [40] found that subjects with moderate OA (KL 1 or 2) increased their isometric quadriceps hamstring ratio by 16% whereas in severe OA (KL 3 or 4) subjects, the latter ratio was limited to an 11% increase. Care must be taken, however, because there is limited evidence that stronger muscles protect against OA progression in persons who have established disease [56].

Asymptomatic and osteoarthritic knee biomechanical data classification

Biomechanical data classification methods aim to distinguish between the asymptomatic and pathological OA knee groups, using pattern classification. There are two major steps in pattern classification: feature extraction and category assignment. The goal of feature extraction is to transform the original data (i.e. spatio-temporal, GRF, kinematics) obtained from gait analysis to a vector quantity which represents individual subject behaviour. The aim of category assignment is to classify each feature which represents an individual subject into one of the two groups (asymptomatic or OA) based on the similarity of the feature with the corresponding group. For many studies, feature extraction represents an important issue, because it is crucial that the gait pattern representation bears as much relevant information as possible to allow proper classification [59-66]. In general, two types of features can be distinguished in gait pattern representation: a local feature which characterizes a gait pattern by parameters measured at specific instants of time on the biomechanical data curve, and a global feature, which, in contrast, corresponds to a global parameter computed throughout the whole data curve. Both local and global features have been used for the classification of asymptomatic and OA knee biomechanical data. For instance, pathological and healthy gait patterns obtained from force platforms were discriminated by a neural network model using a feature vector which contains ten parameters extracted from the vertical GRF [59]. The accuracy of the classification was about 80% [59]. In several other studies, the discrimination of knee OA from normal subjects used the Dempster-Shafer theory (DST) of evidence [60, 61, 63]. The DST transforms the input characteristics into a set of three belief values: a level of belief that a subject has OA knee function, a level of belief that a subject has normal knee function, and an associated level of uncertainty. The subjects' classification uses a combination of the evidence from all the features. The DST studies have investigated various characteristic features: the cadence, the magnitude of the peak vertical GRF, and the knee range of motion in the sagittal, frontal, and transverse planes. The accuracy of the DST method was equal to 96.7% [60]. In a hybrid version of the latter study, principal component analysis (PCA) was used as a data reduction tool in conjunction with the DST to improve the level of accuracy to reach a value of 97% [63]. Although the use of local features in earlier studies helped to assign individuals to an asymptomatic or OA group, this method fails to detect different levels of severity of OA. Recently, Mezghani et al. [65] developed a global feature representation of the individual associated with a nearest neighbour classification method to help distinguish asymptomatic from OA knee gait pattern. The global feature contains 100 parameters that represent the coefficient of the wavelet decomposition of the vertical, anterior-posterior as well as the medial-lateral GRF. Using this global feature, the authors [65] reported an accuracy level of about 90%. Although this value, 90% accuracy, seems lower than that found in a previous report [60], it helps to distinguish between the severity of OA. In fact, the OA severity was further divided into two categories, resulting in a hierarchical classification [65]. The OA patients were grouped into two OA severity categories according to the KL scale: KL grades 1, 2 for the first category, and grades 3, 4 for the second one. The latter method enables the classification of OA graded 1, 2 and OA graded 3, 4 with an accuracy of 77%. This result is in agreement with a recent study by Sen Köktas et al. [66] who reported an accuracy level of 80% with OA patients divided into four categories of severity including asymptomatic. A global representation has also been used for feature characterization of knee OA accelerometric tibia signals using classical Fourier decomposition [64]. Although the accuracy was not reported in this study, the vertical acceleration component, which describes the instability and the alteration in the transmission of shock during walking, was found to be a potent discriminant of knee OA patients from asymptomatic subjects.

The above studies demonstrated the validity of both the features and the classifiers for automatic classification of asymptomatic and OA knee gait patterns as well as for analysis of OA severity. The high classification accuracies, sensitivities, and specificities demonstrate that the developed classification methods can be used to support orthopaedic surgeons when making clinical diagnoses of OA.

Impact of the improved biomechanical knowledge of osteoarthritis on clinical outcome

Biomechanical knowledge has grown exponentially in the last decade. Many highly sophisticated techniques such as 3D magnetic resonance imaging have been developed that allow a very precise assessment of knee kinematics, contact zones of the cartilage, and quantification of cartilage loss (see Chapter 8 – *Quantitative magnetic resonance imaging in the evaluation of structural changes in knee osteoarthritis patients*). All these techniques bring valuable information about the pathogenesis of OA to the scientific community.

Clinical assessment allows diagnosis and symptom assessment, whereas biomechanical assessment provides insight into knee function. Research has shown a relationship between altered biomechanics and degenerative changes in the knee, which in turn raises questions about the protective role of the joint structures during functional tasks. Nevertheless, it is important to acknowledge that different types of data can be acquired in gait analysis and that each type of data provides different information on biomechanics or limb function. For example, spatiotemporal parameters may indicate how patients adapt their gait pattern to pain and disease. Moments and vertical force measurements help to interpret this adaptation in terms of movement strategies. Kinematic data, in turn, seem to be appropriate for monitoring gait adaptation over time and to identify abnormal movements that could be corrected by proper physiotherapy. However, EMG data are necessary to identify the ‘guilty’ muscles [7].

The time has now come to integrate biomechanical with clinical assessment. It is recognized that this could be valuable for the objective assessment of treatment options (either conservative or surgical). Biomechanical assessment also allows an understanding of the underlying factors causing the progression of the disease. The modifying factors are those that are targeted by biomechanical measurements, even before the disease has caused irreversible damage to the joint. Thus, interventions can be developed that address this specific question: Is it possible to change joint biomechanics before it is too late and, if so, how should it be done?

One remaining problem is the applicability of current biomechanical techniques to the clinical context. In modern society, reduction in health costs is an ongoing concern. Therefore, there is a strong need to develop technologies in addition to computed tomography scans and magnetic resonance imaging that are capable of providing precise, complementary, and value-added information. The use of low cost gait analysis is very promising. However, some researchers still point out the difficulty of interpreting such an overwhelming amount of information as that provided by gait analysis. This could be overcome by the use of computer-aided systems to assist with recognizing patterns within very complex sets of data. Techniques originating from the pattern recognition field, such as neural networks, fuzzy logic, and PCA, could be used to reduce data dimensionality and facilitate the classification of massive data sets in terms of movement patterns.

In the coming years, the research agenda in this field could be three-fold: firstly, to assess knee biomechanics pre- and post-treatment (physiotherapy and surgery) and compare different treatment options; secondly, to integrate biomechanical assessment within clinical guidelines and clinical practice; and finally, to improve automatization of multidimensional and complex data analysis in order to assist clinical interpretation of results.

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