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Pose Temporal Estimation in Markerless Normal Human Gait integrating Kinematic Patterns and Segmented Video

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Juan Camilo Lozano Carrillo

Abstract

Human Gait Analysis have become in a relevant field and its findings have been incorporated to the clinicians' daily routines. Human Locomotion is evaluated, usually, in laboratories and with the corresponding protocols, some issues of the kinematics processing need to be attended, particularly because although there have been developments in analytic tools, some particularities of the technique lead to error and different opinions depending on the expertise of the health professional. The aim of this work is integrate information from two sources, kinematics patterns and markerless video. Two sets of information are evaluated: normal subjects and Parkinson's dissease patients.
Keywords:Human Gait Analisys, Markerless Analisys, Pose Recovery, Parkinson disease, Neurodegenerative diseases

Resumen

El análisis de marcha humana se ha convertido en un campo relevante y sus desarrollos se han incorporado a la cotidianidad de los profesionales de la salud. El movimiento humano es evaluado, usualmente, en laboratorios con protocoles correspondientes, algunos asuntos del procesamiento de información cinemática necesitan especial atención, particularmente porque a pesar que se ha avanzado en herramientas analíticas, algunas particularidades de la técnica conllevan a error alto y a diferentes opiniones dependiendo de grado de pericia del experto. El objetivo de este trabajo es integrar información de dos fuentes: patrones cinemáticos y video sin marcadores. Dos conjuntos de datos fueron evaluados: sujetos de control y pacientes de parkinson.
Palabras Clave:Análisis de Marcha Humana, Análisis Sin Marcadores, Estimación de Posturas, Enfermedad de Parkinson, Enfermedades Neurodegenerativas

Contents

1 Theoretical Framework

1.1 Clinical Gait Assessment

Historically, biomechanical studies can be found in classic Greece and Rome were representation of human body reflected a coherent relation of body and different motion activities. Renaissance included dissection and rudimental measurements, prominent studies were carried by Da Vinci, Newton and Boreli, in the nineteenth century the Weber brothers from Germany performed the first formally biomechanical investigation [28]. Since then Gait Analysis is composed by three main areas; namely: Kinematics, Kinetics, Energy consumption indicators; and its interaction with engineering mathematics.
In 1983 it was suggested that the term "Gait assessment" should be applied to the entire process of a person examination and the suggestions and treatment. While the term "Gait Analysis" may be used to refer to the technical side of the gait assessment [23]. Though, those terms are not universally accepted, are useful to make a distinction between the overall clinical examination and the part that takes places in a Gait Laboratory provided with different type of technology to obtain data.
Gait assessment has three basic and fundamental elements: History and Physical Examination and Special investigation [28]. The first involves Clinical Record consultation, possible causes of the motion disorder such as traumas or previous surgery procedures. Physical examination aims to observe under a multi systemic view, but special attention is musculoskeletal system captures special attention, looking for motor control failure, muscle weakness and bones deformation. Those two elements are present in every clinical routine, the special investigation is used as complementary information, generally consists in sensing information from multiple sources in a facility conditioned for this purpose: The Gait Laboratory.
The multimodal information obtained in a Gait laboratory is summarized as Kinematics, Kinetics and Energy consumption indicators. In addition to the source of information present in Gait Laboratories, this chapter covers the most relevant aspects of mathematical tools for human locomotion analisys, in the subsections 'Anthropometry' and 'Analysis Tools'; then a more detailed insight to clinical practice and gait analysis is presented in subsection 'Gait Analysis and Clinical relationship', finally Parkinson's disease overview is covered in the last section.

1.2 Human Gait Analisys

The comprehensive study of human locomotion is known as Human Gait Analisys, this field involves a wide variety of movements that are generated by the synchronization of biological subsystems. Traditionally, the analysis of human locomotion is performed merely using the observation of the clinician [17], representing a considerable difficult challenge particularly because of the quantity of data involved [30]. Biomechanics is a science branch that describes, analyzes and assesses human motion information using automatized methods, in other words it reaches a supervised human gait analysis, becoming an important tool for health professionals, being or particular interest in the following areas: Orthopedics, Sports, Surgery, Rehabilitation, Therapy and Sport Equipment Design.
There is a variety of sources of information in Human Gait Analysis, usually in conditioned laboratories a person is asked to walk while different sensors are capturing data. The human motion information varies between description, monitoring, and analysis. A first aim is to know the position of a person at a particular moment, the term monitor refers to a description over the time, while analysis implies the use of mathematical operations or the combination of information from different sources in order to obtain a parameter that cannot be directly measured and is also informative.

1.2.1 Kinematics

Kinematics refers to anatomical relationships measured over the time, it includes linear and angular movements, velocities and acceleration [29]. First reported kinematic measurements took place in France by Marey and in the United States of America by Muybridge in the 1870s using still cameras[11], later with the development of cinematography cameras the accuracy improved, but the major development to obtain kinematic parameters were computers, thus in early 1980s television cameras linked to computers performed relatively fast calculations. Kinematics are obtained using a diverse set of direct or indirect techniques and then focusing in body landmarks, e.g. center of rotation joints or the edge of the limb segments. There are direct kinematic measurements performed through goniometers, acelerometers and other transductors attached to the body.
Imaging measurement techniques on the other hand provide a more complete view of the region of interest. Traditionally, bright spheres are located in very specific body parts in order to measure the location and inclination of particular anatomical regions. This type of Marker Analysis is restrained to specific annotated regions. As with many other biological data, the capture is noisy and the natural walk gestures are affected by the interference of the markers[2]. Development of informatics in late 20th century; leading to higher computational performance and the reduction of devices' cost; allowed the emerge of Markerless Analisys techniques that has become an alternative with promising successful results. As inferred

from the name, these methods do not place artifacts over the body, the person is recorded in a more familiar situation and video processing techniques are applied to recover kinematic information.
Due to the large quantity of input data usually kinematic data is studied in two-dimensional planes, Figure 1-1 illustrates the 2-D planes, while Figure 1-2 presents the typical sagittal plane measurements of a normal person's Joint Angles, exactly Hip, Knee and Ankle.

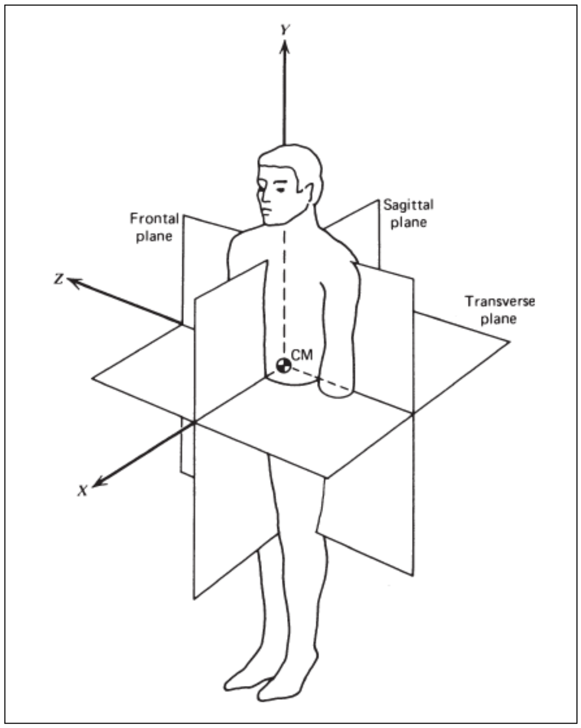

Figure 1-1: 2-D Planes tiically used in Human Gait Analisys [29]

Marker based Kinematics

Last three decades of informatics and video recording advances have provided the conditions to perform indirectly measurements over the body, not only in specialized research university groups but also in many health care facilities becoming familiar to many physical therapists and related health professionals. One essential parameter to obtain useful clinical data is spatio-temporal location of the body, with camera calibration data and a body representation of line segments and joints, limbs are located in a 3-D coordinate system knowing the position of a reduced quantity of anatomical areas; considering anatomical restrictions and trigonometry; angular information complete the limb segments spatial localization, those anatomical areas that are key to describe limbs' location are marked with some high contrast material attached to the body. Historically, starting as universities group research efforts, videotapes that needed to be digitalized and then transferred to a computer were

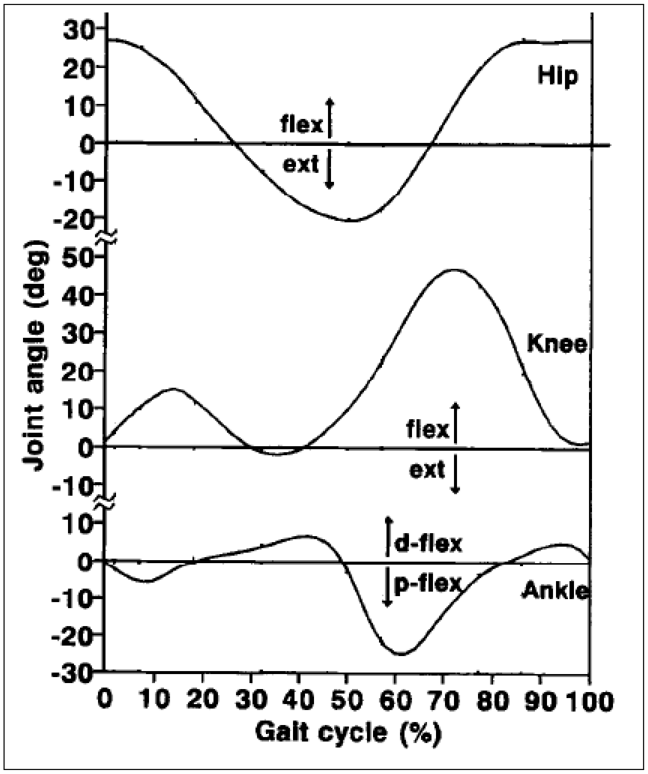

Figure 1-2: Sagittal plane Joint Angles by normal people during a Gait Cycle [29]

the most advanced option to perform this type of analysis, different alternatives where implemented leading to different type of markers, some of them designed active markers using light emitting diodes, others took advantage of reflective material placing it over spheres, forming passive markers. Due to the novelty few groups developed their own protocol, this providing unique characteristics including measured variables, degrees of freedom and notation. The "Newington model" is the pioneer and most used, being the base for commercial packages [10]. Other relevant protocols are the developed by "Servizio di Analisi della Funzione Locomotoria", "Calibration Anatomical System Technique" (CAST) and "Laboratorio per l'Analisi del Movimento nel Bambino".

Markerless Techniques

In recent years sensor and computational advance has allow techniques that do not use markers to establish the body mechanics, on the other hand, shape and anatomic relationship are promising. Though there is no standard to follow as in the marker based case, imaging usually consists in four main stages, Model initialization, Visual Feature extraction, tracking, and Feature analysis. After video recording, the Model establishes the constraints and set the parameters of forces, limb length and angles through a biomechanical representation, feature extraction selects the relevant visual information frame by frame, temporal variation is fundamental to obtain Gait analyzable data being Tracking the respective stage where information in delimited temporally, finally trough statistic and mathematical methods Feature Analysis is achieved. The challenge of these techniques is rather related to computational video processing constraints and occlusion.

1.2.2 Kinetics

Kinetics measures the Forces during gait, using customized transducers. Kinetics considers both the inner tissue forces and the external ones, v.g. the force produced on the surface when the foot lies on it or passive loads like wind resistance. Already by 1970s accurate 3-D sensing devices with electrical output and high frequency response were available. Some studies in animals have explored surgical techniques that implant transducers 'in vivo', however for evident reasons these approaches can not be implemented in human. If proper kinematic information is known, as well as some anthropometric data and external forces, it is then possible to obtain the inner muscle-tendinous forces, using a prediction Inverse Solution with a biomechanical model. Recent kinetic works also include limb acceleration and information of joint moments and joint power.

1.2.3 Electromyography

Electromyography measures the electrical activity of the muscles, the contraction of a muscle has an electrical signal produced by the potentials of the muscle fibers. A motor unit action potential is simply the electrical activity associated to a set of muscle fibers that are connected to a single neuron and depending on the muscle specialization can go from a couple of fibers to hundred of them. The electrodes located on the skin or inside the body calculate the algebraic sum of the nearby motor unit action potentials. The graphic representation of this signals along the time is called Electromyogram (EMG) and the systematic study of this signal is Electromyography, early investigations of this kind were performed by a research group in California in the 1940s and 1950s, since that experimental beginning, nowadays it has become a widely accepted and performed routinely in gait analysis laboratories. A considerable variety of models have been proposed to interpret and associate the potential values and the state of the muscle.

1.2.4 Anthropometry

Anthropometry is the field that studies physical measurements of the human body to determine characteristics and differences between individuals and groups. Traditionally as part of the antropology evolution and etnic research, the anthropometric field has expanded to human-machine interface, space design, armors and similar. Although it is clear that there are differences according to gender, body building and racial origin, in absence of direct body measurements an average of body proportion was presented by Drillis and Contini (1966), and illustrated in Figure 1-2.

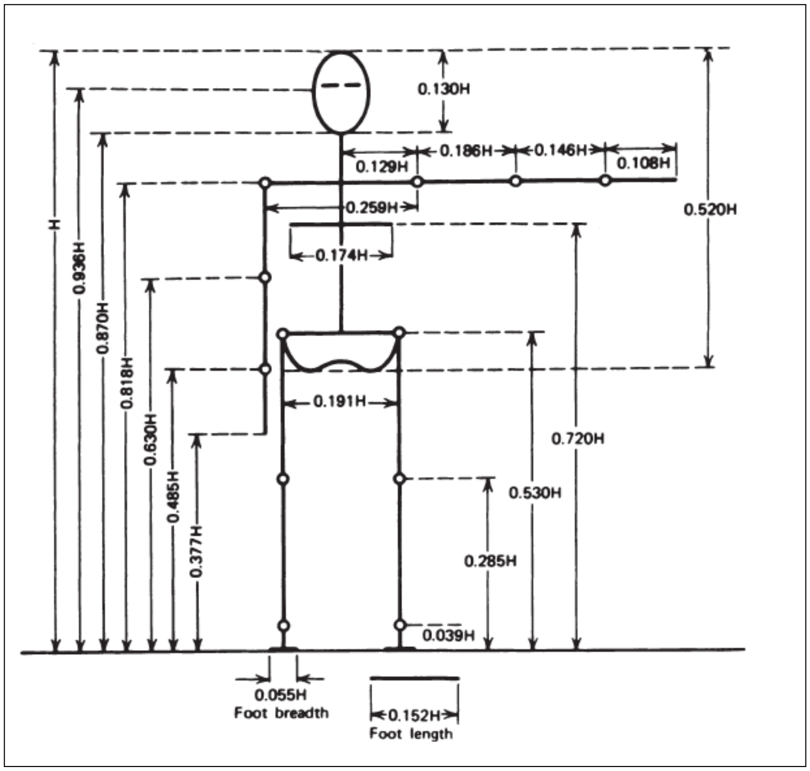

Figure 1-3: Body segments with respect to the Height H [8]

1.2.5 Mathematical Analysis Tools

No matter the sensing method, the biological signals obtained in the laboratory are time-varing and have to be treated like any other signal. Many times research involves the comparation between one signal point and the past, present and future values of another signal. The cross-correlation evaluates how the relationship between two signals is. The Pearson Moment Correlation Factor (Eq. 1-1) is a well known statistics and is a measure of the statistical relationship between two sets of data. It determines whether the variables x and y increases or decreases together (positive correlation) or if x decreases when y increases (negative correlation). The correlation coefficient indicates the strenght of the relationship and is a normalized dimensionless magnitude between -1 and 1.

In the Pearson product moment correlation coefficient, X_i and Y_i are the i^th samples of x and y, and $\bar{X}$ and $\bar{Y}$ are the respective means. S_x and S_y are the standard deviations. The numerator of this formula is the product of the difference of the variable sample and its respective mean, if the two variables are not related, the x against y graphic would be scattered points all over the x-y plane, the sum of the consecutive product would be close to zero, on the contrary if there is correlation the $(X_i - \bar{X})$ and $(Y_i - \bar{Y})$ fall in one line in the x-y plane, obtaining a finite value in the summation, the effect of the number of points is suppressed dividing by N, an finally it is normalized between -1 and 1 dividing by the $S_x S_y$

$$r = \frac{\frac{1}{N}\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{S_x S_y} \tag{1-1}$$

1.2.6 Gait Analysis and Clinical relationship

Gait analysis is rarely used to make medical diagnosis, the quantitative information provided is used as a medical paraclinic to prescribe treatment and evaluate the improvements. [25]. The main clinical value of Gait Analysis is present in central nervous disorders associated with spasticity, particularly cerebral palsy in infants. The main goal is to provide reliable information that help the clinician to take a decision about performing surgical interventions. As reported by DeLuca, Kay, and Fabry et al, the initial surgical intevention decisions were changed after considering Gait Analysis data [7] [14] [9]. The success of the spastic cerebral palsy surgeries introduced the gait analysis information is 14 in 16 children as reported by Lee et al [16]. The psychological improvements are also part of the benefits of the Human Gait Analysis. Not all the parameters of a person's motion analysis must be used, the ability to detect the relevant information remain being part of the clinician discretionality. For neorological origin locomotion disorders the gait variability is itself an indicator of the severity and level of the disease [12]. Knowing quantities of the patients motion state can help to estimate the effects of medication or other forms of treatment. Clinical motion research has been proved used also in a wide variety of disorders in other fields such as rheumatology, orthopedics, endocrinology and neurology [13] [20] [21] [26] [4].

1.3 Parkinson's Disease

Parkinson's Disease (PD) is a the second most common neurodegenerative disease, after Alzheimer's disease , PD is characterized by the death of selected population of neurons, among others the dopaminergic areas in the substancia nigra are susceptible and loss is estimated to be 60 to 70 percent at the time of symptoms observation [15]. The disease is manifested as a disabling disorder observed in a wide range of the population including young people [27] [1], accurate diagnosis is critical and remain based on clinical grounds with no specific diagnostic test is avaliable[19]. The epidemiological figures present variable diagnostic criteria and study population, nonetheless a prevalence of $\sim 1\%$ to $\sim 2\%$ in the population older than 60 years or $\sim 0.3\%$ of the general population is accepted. PD cause is unknown but interaction between genetic and enviromental factors are probably involved, thus the exposition to pesticides and other toxics, family history and age are the widely documented so far, this disease exhibits a male-to-female ratio of 3:2 in most of the studies.

Motor symptoms include four main features: Bradykinesia, rest tremor, rigidity and postural and gait impairment.
-**Bradykinesia:** Is the loos of amplitude or speed during attempted rapid movements.
-**Rest Tremor:** Is an oscillatory involuntary movement that appears when the affected segment is relaxed and supported by a surface. Rest tremor is usually in the mid-range from 3-6 Hz with variable amplitude from 1cm to 10 cm.
-**Rigidity:** Refers to increased muscle tone felt in the examination over a passive movement of the affected segment, limbs or neck.
-**Postural and Gait Impairment:** Loos of postural reflexes, in some cases extreme truncal flexion forward. There is also decreased arm swing resulting in slow and transformed in multiple small steps.
Non-motor symptoms are also perceived after years of PD presence, thus cognitive decline, depression, autonomic absence, pain and sensory symptoms.

1.3.1 Diagnose and clinical treatment of Parkinson's Disease

The only reliable method to diagnostic PD is assessing Lewis Bodies in the Substantia Nigra during an autopsy [24]. In the clinical praxis it relies strongly in the expertise of the physician or physical therapist, being difficult to assess in early stages. Progress of PD is evaluated with UPDRS (Unified Parkinson's Disease Rating Scale), which consideres among others, cognitive abilities, daily task performance and rigidity. Other scales are "Hoenh and Yahr" and "Schwab and England Activities of daily living". "Hoenh and Yahr" scale considers the advance of the disease according to the side affected and the autonomy of the patient, despite the effort of defining protocols, evidence have prove that some diagnostic could not be proven with autopsy .

2 Research Problem and Methodology

This Chapter covers the proposed framework for this project: the research problem, objectives and activities are presented. First, the research question and problem are discussed, the chapter proceeds with the description of the proposed methodology, then the testing setup and experimental observations are explained.

2.1 Research Problem

Traditionally Gait Analysis involves different sources of information, Kinetics have tried to determine the origin of the forces that take part in locomotion, while Energy Consumption Indicators are another recurrent parameters analyzed frequently used in muscular system studies, finally Kinematics is one main branch and provides an important source of information to health professionals, being studied from different perspectives. Direct observation requires high skilled personal and there is still high variation on the appreciation on a daily basis clinical work due to the subjective method [29]. Then, there is a range of technology tools that have allowed to reach more precise considerations, from direct measurement; obtained, for instance; from a Goniometer in anatomical segments; to photogrammetry measurements, Markers approaches have led Kinematic observation [11]. Despite its widespread usage, there are some considerations that need to be mentioned, this technique; as other direct measurements; alters the natural gesture of the Human Gait and also there is inherent disturbances in the measurements due to the placement of the markers in soft tissue [2]. Indirect measurements also face challenges, markerless approaches need to deal with video processing techniques face occlusion issues, environmental and lighting conditions as a source of noise and computer algorithms have to be robust and adaptable to the wide range of human particularities and traces. This work propose integrate kinematic information that comes from direct measurement and indirect to enhance the perspectives of unsupervised computational analysis. The research question faced is: **How to perform a markerless analysis integrating prior kinematic patterns with a body segmented from video?**

2.1.1 Objective

Integrate kinematic *a priori* patterns with gait videos within a markerless analysis to obtain precise localization and detection of lower limbs in a gait cycle.

2.1.2 Specific Objectives

1. Develop a temporal human posture model during a gait cycle using kinematic *a priori* patterns
2. Capture gait Spatio-temporal patterns segmenting markerless video recordings.
3. Integrate the information from the human posture model with the segmented video,this way enhancing the markerless approach.
4. Validate the testing and experimentation methods.

2.2 Methodology

Kinematic prior information is used to obtain a Map of Poses, in other words a representation of the human body as a set of possible postures given lower joint angles, a biomechanical second order model proposed in a Biomedical Engineering Master thesis by Romero, Cifuentes and Martinez [18] provide the prior angle lower limbs joint patterns used to create a set of postures each percentage of the gait cycle, those one hundred postures are recreated using a human model built with enlarged segments that considered the anthropometric parameters. Two sets were analyzed in this project, normal control subjects and Parkinson's disease patients at stage II and Stage III, the methodology is applied independently though it was tested in both normal and pathological gaits.

Simultaneously, from markerless video a geometrical representation of the body is obtained, that process requires the delimitation of the body shape through foreground and background determination, background subtraction (BS) algorithms most general idea consists in compare one frame with a background model and pixel variation indicates foreground assigning 1 to built a binary image with background values being 0 [22],a fundamental aspect is how to determine the background model and consider the variation in brightness and translation of the camera, so Background Model may be dynamical. Among others, Background Subtraction models proposed and generally used include Running Average, Gaussian Models, Gaussian mixtures and $\Sigma - \Delta$ [5]. Two types of Background Subtraction algorithms were tested in this project, $\Sigma - \Delta$ and ViBe. $\Sigma - \Delta$ BS is based in the $\Sigma - \Delta$ Modulation well known for its computational efficiency. This modulation samples the signal at higher rates than the specified by Nyquist theorem, achieving strongest correlation among adjacent samples, thus the quantization error power spreads over a wide range while the the signal power remain within the signal band, allowing good signal-noise separation from the quantization noise [6]. ViBe Algorithm proposed by Barnich and Von Droogenbroeck consists in compare frames with a model in a RGB space and a sphere of closeness, if the frame pixel is located insede the Background model sphere in the RGB space then that frame is assumed to be also part of the background. The model is updated in time. [3].

Then based on lower limb minimal loss of details ViBe was choosen. Once the region of interest is selected in the video, gait cycles frames need to be carefully chosen, heel reaching the floor surface is the indicator either for the beginning or ending of the cycle, using thirty frames per second might complicate this action and a point immediately after heel strike shall and adjust later that displacement in the cycle. Once the cycles are delimited, each shape is located into a Bouding Box, for each experimental of the two sets of information; one is the normal and the other is the pathological gait data; the maximum silhouette values are finding by selecting the highest height and the swing phase moment when the legs are completely apart from each other. Once the maximum silhouette region is known, a normalization process is performed, all the cycles heights are normalized respect to the maximum silhouette region, this is particularly necessary for similarity metrics that are sensible to position of the image regions. Once last consideration was carried in this phase, a preprocessing stage was made, mathematical morphology tools, particularly opening and closing enhanced the lower limbs information which after background subtraction and for environmental reasons were affected and diminish in the process.

Integration of the information used a ground truth, the information assumed as more accurate, to do so, each silhouette from the markerless video cycles were matched to a pose from the Map of Poses, the matching was performed carefully and in the process there were consideration not only of similarity but also cycle progression, important to notice that in this part of the methodology the non-linearity of the human locomotion was observed, the fact was that for some people right foot standing phase was longer while in the swing phase postures of the Map of Poses increased faster. A silhouette to silhouette comparison is performed, a new video of a sagittal plane gait with no kinematic information is compared with the trained data, the most similar matched silhouette will pass the pose to the new video frame, and with the pose subsequently angle pattern data is associated this time not directly from an expert but from a comparison algorithm, being that the core of the idea proposed in the objective of the project, to enhance localization and to obtain accurate measurements of angle on markerless video. The comparison silhouette to silhouette methods proposed and then tested were two, one analyses the general characteristics of the body shape, that is a regional consideration which resulted being highly dependent on the bounding boxes and its logical and coherent placement previous the comparison. The other similarity metric explores the geometrical relations among different cycles, but this time the comparison is not easily affected by the direct placement, since the center of mass is geometrically located in each silhouette and then successive summaries in a polar coordinate system for each degree. After a whole 360-degree space covering, each silhouette have been transformed into a space where a Pearson Correlation is the similarity indicator.
The information integration is validated using the described patterns in biomechanics for normal behavior, while for the pathological gaits a measurement took place using markers, that information allows us to obtain an indicator of accuracy respect to one method widely

used in gait analysis. A summary of the proposed methodology is presented in figure 2-1.

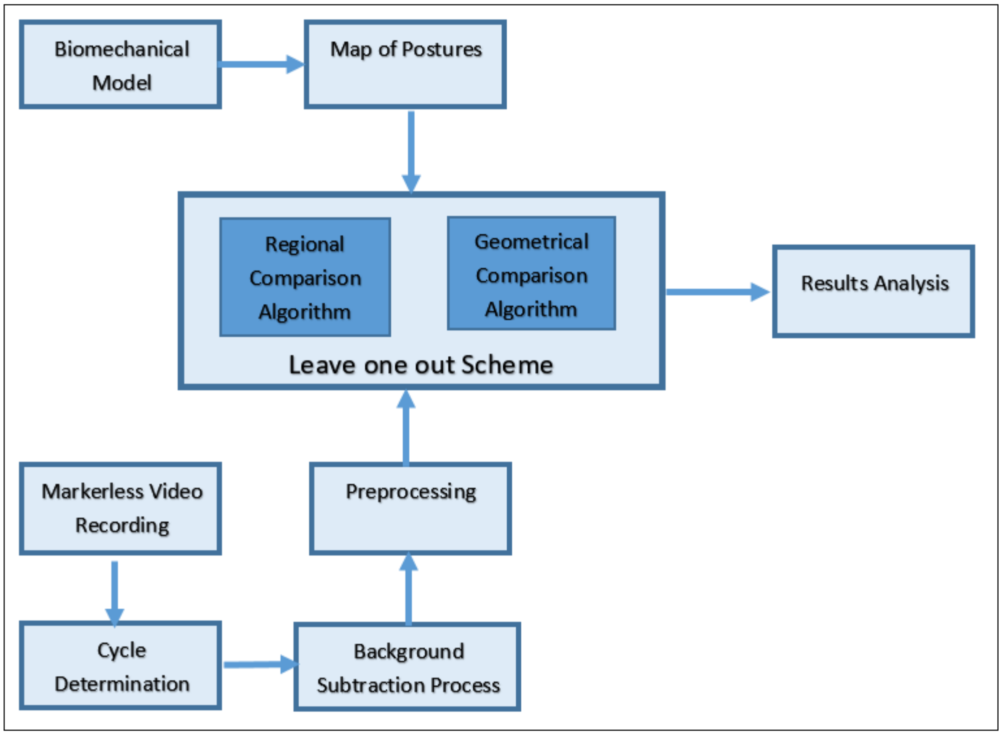

Figure 2-1: Methodology Flow Diagram

2.2.1 Activities

- Delimitation the scope of the human model: This activity included the selection of the human prior to model information in the sagittal plane, that represents relevant indicators such a joint flexoextension movements, being the lower limbs and the Hip and Knee patterns useful and well known in clinical context.
- Generation of the normal gait Map of Postures: Using the biomechanical model and its resulting angle patterns a human link-model is created, all of the one hundred poses constitute the Map of Poses for normal testing.
- Generation of the pathological Map of Postures: Similarly to the normal gait case, the biomechanical model may also recreate gait patterns for hip and knee, another set of one hundred poses is then obtained.
- Markerless Video Capturing: At UN Gait Laboratory a process of video recording took place, ten normal control subjects and ten parkinson's disease patients were gathered at Medicine Faculty in BogotÃ¡ and they agreed the protocol of measurements, they signed a consent and shared their data knowing that it would be used for academic

purposes. The subjects wear tight clothes and the color used were green which provide high contrast respect to the white wall of the Gait Laboratory.

- Cycle Delimitation: When the video was stored and identified properly, cycles were specified through the heel strike reaching the floor, this project considers the right lower limb for analysis, notice that gait is a rhythmical and periodic movement [], it is possible to propose the assumption that right and left limbs are similar with a difference in phase of 50 percent of the cycle and still preserve high accuracy. From each patient two cycles were selected to become part of the video data set.

- Background Subtraction Process: Two algorithms were tested, classical Sigma-Delta and ViBe, the latter is open to academic projects and was developed by Olivier Barnich and Marc Van Droogenbroeck, ViBe recovered better the foreground information this is because the segmented body shape preserve feet data, while the sigma-delta tend to have a loss in that key anatomical segment for this project.

- Preprocessing: Human body shapes were located in Bounding Boxes, this delimits the area of interest to a specific and known area, besides regions of interest, silhouettes have to be comparable so a normalization in height was performed and then Mathematical Morphology closing and opening operation enhanced the final human body silhouettes that are delivered to the integration information methods.

- Silhouette Training: A Leave One Out scheme was proposed to validate the methodology that enhances new markerless videos with prior kinematic information, this scheme requires all the cycles to be trained in this case each silhouette is associated to one of the Poses of the Map of Poses. One of the trained cycles is said to be Out, each of the frames of that Outed Cycle is compared with all the frames of the trained and included cycles. Normal gait set is composed by 18 cycles for 9 patients, looking forward to avoid biased results each cycle leave out also the another cycle of the same subject, this is each outed cycle search similarity with a number of 16 cycles. After 18 repetitions results are ready to be analyzed. Pathological case was divided into Stages II and III, ten cycles from five patients each, and the same anti bias precaution was applied. One important remark to mention in this point is how the association shows the non-linearity of the motion, some particularities of the gait imply the non equal variation on the frames over the percentage on the cycle, for instance in the right foot support phase one increment in frame resulted in steps equally distanced on poses from the map, while in the swing phase the accelerated and decelerated reported behavior represented irregular steps in the change of pose from the map of poses,

- Regional Comparison Algorithm: This integration method considered a pixel by pixel comparation, the general idea is quantify three regions when comparing two silhouettes, one that is common to both silhouettes or in other words the overlapping region, Yt, the other two regions are the non-overlapping regions of each silhouette, Rt and Bt, to do so, first it was required matching carefully the each boundind box, this was placing the region of interest to the right and the blank space to the left, vertically all silhouette covered the same space. Once the matching was done, a similarity metric is proposed, equation 2-4 is supported by equation from 2-1 to 2-3.

$$Rt = \sum_p M_A(p)(1 - M_B(p)) \tag{2-1}$$

$$Bt = \sum_p M_B(p)(1 - M_A(p)) \tag{2-2}$$

Having two silhouettes A_i and B_i that are being compared, functions Rt and Bt are a per-pixel p calculation of the information solely in silhouettes A_i or in B_i, respectivelly: And then a function Yt computes the overlapping between the two compared silhouettes as:

$$Yt = \sum_p (M_A(p))(M_B(p)) \tag{2-3}$$

Finally, the similarity metric is approximated by the fraction, notice that this is a spacial comparison so the matching is a key aspect for the good performance in this point, the comparison metric takes the minimum value and it requires not only having high overlapping region but also computes the not shared pixels and expects that those two regions to be little. a is a coefficient that allows to give more weight to one of the two silhouettes, either A or B and penalize higher if one of the non-overlapping areas results significantly higher than the other two quantified regions:

$$(a)\frac{Bt}{Bt + Yt} + (1 - a)\frac{Rt}{Rt + Yt} \tag{2-4}$$

After testing a values from 0 to 1 with steps of 0.25; 0.5 exhibited best performance achieving the best results, there is no reason to privilege the trained silhouette over the silhouette that have no pose information associated, the information that they are not sharing compared with the overlapping area is then equal no matter from which silhouette comes from.

- Geometrical Comparison Algorithm: This algorithm is translational invariant , it is certainly sensible to rotation over the center of mass but that kind of movement is assumed to be nonexistent in the scope of gait and the matter of this project. The idea is to calculate the geometrical centroid, in a plane the centroid is the arithmetical mean position of the points of the shape, the centroid of the human body shape is corresponds to the Center of mass, assuming uniformity of the body density and having constant Gravitational Field, the Center of Mass is the same Center of Gravity the point where the Gravity force applies its effect on the whole person. Having both, a geometrical consideration or statics perspective and a force consideration or dynamical perspective, the centroid is a fundamental point, that considering some assumptions, comprehends human locomotion for some analysis. This project is comparing human silhouettes of people walking and reproducing gait in similar Static and Dynamical conditions, considering that the centroid is the key point to establish the geometrical comparison, once the centroid is located for each frame, the silhouette is mapped to another space, consecutive line integrals are calculated having steps of one degree from 0 to 360, thus covering the whole image. In 2-5 equation the transformation is specified, in 2-6 equation the mathematical formulation for each line direction is reported.

$$F(\theta) = \int_C f ds; 0 \leq \Theta < 360 \tag{2-5}$$

$$\int_C f ds = \int_a^b f(r(\theta))|r'(\theta)|d\theta \tag{2-6}$$

Once all the silhouette are transformed, the similarity metric chosen was the Pearson's Correlation coefficient, this mathematical tool is invariant to the magnitude of the functions being compared, this coefficient represents similarity over the X axis of the functions being compared, simultaneous increments or decrements provide positive PCC, the closer to one the more similar the functions are, in this case what was compared where silhouettes in the defined space.

$$\rho(\theta) = \frac{\frac{1}{N}\sum_{i=1}^{N}(A_i - \bar{A})(B_i - \bar{B})}{S_a S_b} \tag{2-7}$$

- Leave One Out Scheme Testing: The activity "Silhouette Training" was the first part of the Leave One Out Scheme for validate the proposed methodology, as it was stated in that section one cycle is left out of the cycles that have kinematical information, each frame of the outed cycle is compared with the whole set of frames from the cycles that have been associated to poses from de Map of poses, the most similar silhouette from the trained data delivers and assigns its kinematic information to the frame from the outed cycle, when all the frames are compared kinematic information for that cycle have been associated and consequently the lower limbs located spatially. Then the outed cycle enter to the trained set and another cycle is left out. When all the cycles have been left out, the test finished.

3 Human Pose estimation during normal and pathological gait analysis by fusing Prior Kinematic Patterns and Silhouettes descriptors

The complete Results Analysis and Perspectives are found in this chapter, that consists in an article submitted to a peer-reviewed journal, one fundamental aspect in research field. The article is titled "Human Pose Estimation of Normal and Pathological Gaits by Fusing Kinematic Patterns and Silhouette Descriptors" and was submitted to the Journal "Medical Engineering and Physics". The article contain a fully review of this project, a detailed Results analysis is found in "Evaluation and Results", while the "Discussion" section is a starter point to find Conclusions and future work of this thesis.

Human Pose Estimation of Normal and Pathological Gaits by Fusing Prior Kinematic Patterns and Silhouette Descriptors

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Abstract

Quantification of gait patterns is crucial for assessing and following up motion disorders. A kinematic gait analysis may capture spatio-temporal posture patterns whose characterization and quantification might be useful for improving the current description of a wide range of pathologies. Currently, markerless strategies are appealing techniques that recover human poses by using the recorded video and human shape information. This work presents a novel markerless pose estimation that follows normal and Parkinson's Dissease (PD) gaits recorded in sagittal plane video sequences. A structural kinematic model is run to emulate different gait dynamics allowing to recover a prior represented as a set of synthetic poses. For the whole recorded sequence, a per-frame-human shape is firstly recovered, characterized and mapped to a previously learned space of poses. The most likely pose is then recovered for each frame, until the whole recorded sequence is described and a set of kinematic patterns is computed from the recovered poses. The performance of the proposed approach was evaluated by comparing the obtained sequence with ground truth patterns from control and PD gaits, diagnosed at stage 2 and 3. Experiments were performed with real data from 10 controls and 10 PD patients, considering two gait cycles per patient. The proposed approach achieves an average correlation coefficient of 0.97 and 0.86 for control and PD gaits, respectively.

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I. BACKGROUND

The human gait, that fluid and continuous movement with a natural repeating character, can be understood from complex interactions between musculoskeletal structures that are perfectly coordinated by neuro-motor commands [18, 24]. Estimation of human poses during locomotion simplifies such comprehension by determining a set of relevant spatio-temporal patterns of the different gait variables, namely joint angles, limb velocities and anatomical relationships, among others. These patterns identify and characterize gait pathologies with a certain confidence [15, 16] that makes they might be used as an evaluation base. A sequence of poses can be used as the main source to carried out kinematic analysis in the most important parts of the gait cycle and highlight intra and inter subject differences..

Classically, a gait analysis is carried out using a set of markers carefully placed upon some specific anatomical repairs. However, this conventional procedure is invasive and alters the natural movement gestures, restricting the analysis to a set of temporal trajectories while introducing errors from the variability of both soft tissues and marker locations. [3, 14]. In this context, markerless techniques may be appealing as an alternative that recovers gait motion patterns using only human shape dynamic information. These strategies have successfully labeled activities in outdoor scenes or recognized gestures for identification applications. [4]. From a clinical perspective, these techniques may capture classical patterns while opening the possibility of finding out hidden spatio-temporal relationships during the locomotion. However, such kinematic characterization in clinical scenarios is still an open and challenging problem.

Markerless approaches have used either appearance information or structural and motion priors. Temporal appearance methods have been reserved to applications where a coarse recognition is acceptable and people identification is likely [2]. This is however insufficient for those clinical purposes that demand an accurate joint labeling and following up. Pose recovery strategies, in contrast, have estimated geometrical joint localization using structural prior information. Chengkai Wan et al. recover a human body from an active contour strategy, for which an initial rigid structure formed by line segments is deformed to any possible posture. Such method captures relatively well static poses from a fixed position but the technique is totally appearance-dependent. Lu et al proposed a layered deformable model for gait analysis that integrates poses with silhouettes using a likelihood measure that determines the correspondence of each limb. This approach might estimate some joint angular patterns from the estimated pose but the deformable model could hardly match fuzzy borders in noisy images .

Fathi and Mori split the observed silhouette into a set of patches [Fathi and Mori], each characterized by classical spatial moments. A set of trained patches coupled with artificial poses is used to classify a new video. This approach results sensitive to the captured silhouette angle since moments depend on geometrical transformations while relevant shape attributes may be lost by this local representation. Additionally, Radwan et al proposed a pose recovery strategy from a graph representation using a support vector machine that learns similarity features from videos [22], a strategy that depends on the appearance and the number of samples. Other approaches have used geometrical descriptors in the frequency domain, for a correspondence with a pose map can be established [7, 21]. These approaches however may fail if local changes contaminate observations or background. Additionally, dynamic gait models associate visual poses to particular video-sequences under a markerless framework. Kakadiaris et al uses a classical kalman filter that tracks a 3D human structure [13]. This filter however is a well known first order predictor which could hardly capture important non-linear gait features. In other work, James M. Rehg et al integrate a rigid model of the human body with three synchronized cameras [23], but focusing exclusively on static depth estimations. Additionally, Wachtert and H.-H. track, by using a particle filtering, a rigid body model from different sequences captured with synchronized cameras. This method is computationally expensive and several errors appear when simultaneously tracking the rigid body from different points of view.

This paper presents a novel markerless strategy that follows normal and pathological gaits by mapping the temporal visual descriptors of a particular frame to a previously enriched space of poses. A main contribution of this work is the function that maps a silhouette frame descriptor to a most similar learned silhouette which is coupled to a particular pose. This strategy allows us to quantify different normal and pathological kinematic gait patterns, including non linear features, under a framework that is quite robust to noise. The method starts by firstly building a map of poses for normal and Parkinson's Disease gaits (Hereinafter referred to as PD gaits) during a cycle. A previously developed biomechanical model [17] generates the set of poses that simulates normal and PD gaits which are then associated to the corresponding set of silhouettes obtained from an actual video. The result is that both normal and pathological cycles are described by a set of silhouettes, each with its respective pose. An additional step consists in constructing a silhouette descriptor by identifying local and global features at the silhouette. The local part of the descriptor is composed of those pixels belonging to the silhouette boundary while the global part is defined as the radial distance from the silhouette gravity center to the boundary, in a radial space formed by lines passing through the gravity center every 1°. The descriptor metrics is then defined as a combination of the overlapping degree between two local descriptors and the correlation coefficient between two global parts. The rest of this paper is structured as follows: Section II describes the proposed approach. The evaluation, results and effectiveness obtained by our approach are shown in section III . The section IV presents a discussion and potential future work.

II. MATERIALS AND METHODS

The proposed markerless strategy obtains a sequence of kinematic patterns by selecting the most likely series of temporal poses that can be associated to actual gait videos. Firstly, a space of probable poses is built by running a previously developed biomechanical model [17] that generates sequences of poses for normal and PD gaits (Figure 1 (A)). These successions of poses are then assigned to their corresponding silhouettes, drawn from a set of video sequences during a previous training step (see Figure 1 (B)). For a new gait video, a background subtraction algorithm obtains a coarse human shape from which a global shape estimator and a geometrical characterization are generated for each frame of the whole sequence (Figure 1-C). This characterization is mapped to the space of silhouettes using a pose similarity cost function, composed of two metrics, one that compares regions straightforwardly and a second that transforms silhouettes to an alternative space representation where the most likely pose is determined, as illustrated in fig 3. Once the gait video is completely associated to a set of poses, different kinematic estimators are computed from markerless point of view. The pipeline of the proposed approach is illustrated in Figure 1.

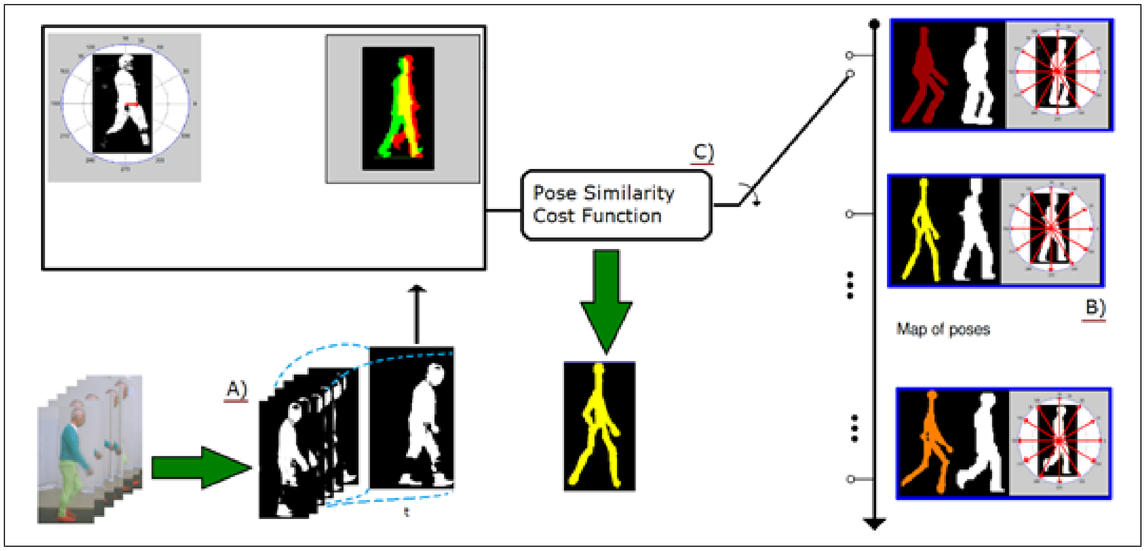


FIG. 1: Pipeline of the proposed method. Firstly, a space of artificial poses is generated by running a biomechanical gait model (B). For a new walking video (A), a background subtraction algorithm recovers a global shape estimator and a geometrical characterization (C), Finally, a family of global and local metrics associates the most probable pose for the previoiusly characterized silhouette.

A. Modeling Poses

Gait is commonly characterized from kinematic and kinetic points of view, facilitating understanding of both gait spatio-temporal patterns and forces that regulate gait displacements [8]. The kinematic analysis describes a wide range of gait pathologies, for instance, crouch gait, cerebral palsy, neurodegenerative diseases and prosthetic movements [12] [4]. Classical kinematic analysis approximates the human body to a rigid structure which describes normal and pathological patterns as a set of joint displacement and movements/velocities of the lower limbs [13]. Such rigid structure P is usually composed of a set of rigid limbs that are articulated by limited joints, reason by which rigid transformations may be considered under Euclidean metrics.

In the clinical practice, such rigid structure is typically recovered for each patient from a set of markers placed on the human body, following specific protocols [Note1] . However, this methodology is quite invasive, requires a large number of anatomical points and alters natural locomotion gestures [3]. The locomotion study has then been restricted to hospital environments with devoted devices and customized spaces that more or less meet what is currently known as gait laboratory. These markerless strategies open up the possibility of studying any disease pattern in no controlled conditions which is closer to the actual disorder patterns.

In this work, this structure P is reduced to four segments that represent the lower limbs, $\{k_1 \dots k_4\}$, and four rigid segments that stand for the upper limbs, from $\{k_5 \dots k_8\}$, while a set of joints couples different limbs with a trunk and head, as illustrated in Figure 2. This structure, hip and left-right knee joints, allows for joint angular measures as $\{A_1(t), A_2(t) \dots A_4(t)\}$. A set of poses, generated by a previously developed biomechanical model [17] defines the whole gait cycle, including the single and double stance. At a any time i, a Pose is defined by its structural and dynamical configurations, represented by the feature vector: $P_i = (k_1, k_2, ..k_{10}, A_1(i), A_2(i), ..A_4(i))$. In Figure 2 a typical recovered pose is shown. The structure P simulates normal and pathological patterns with a reduced set of parameters [11] by fusing real-learned trajectories with a physical representation of locomotion, consisting in a spring mass system coupled to a double inverted pendulum that captures the sequence of muscle activation in the single and double support phases [17]. These poses describe kinematic patterns as the angle trajectory of the right and left hips, or the right and left knee angular trajectories or even more, the velocities and accelerations of each limb.

B. Video Data Segmentation

A coarse human shape is recovered by a background strategy that obtains a silhouette per frame. The Visual Background Extraction (ViBe) algorithm was herein applied because this strategy has demonstrated accurate foreground detection in several applications [6]. In the ViBe approach, each pixel is mapped to an Euclidean color space (ECS) and compared with a background pixel model, represented by the set of neighboring pixels in the previous frame. The foreground/background labeling of each pixel is then defined as the pixel cardinality w.r.t the set of neighboring pixels in the precedent frame, i.e., the number of background pixels that matches within a radius R and w.r.t to a previously selected threshold t. The whole silhouette sequence is bounded and normalized in the space of poses. A set of poses captured with ViBe approach is illustrated in Figure $3-b$.

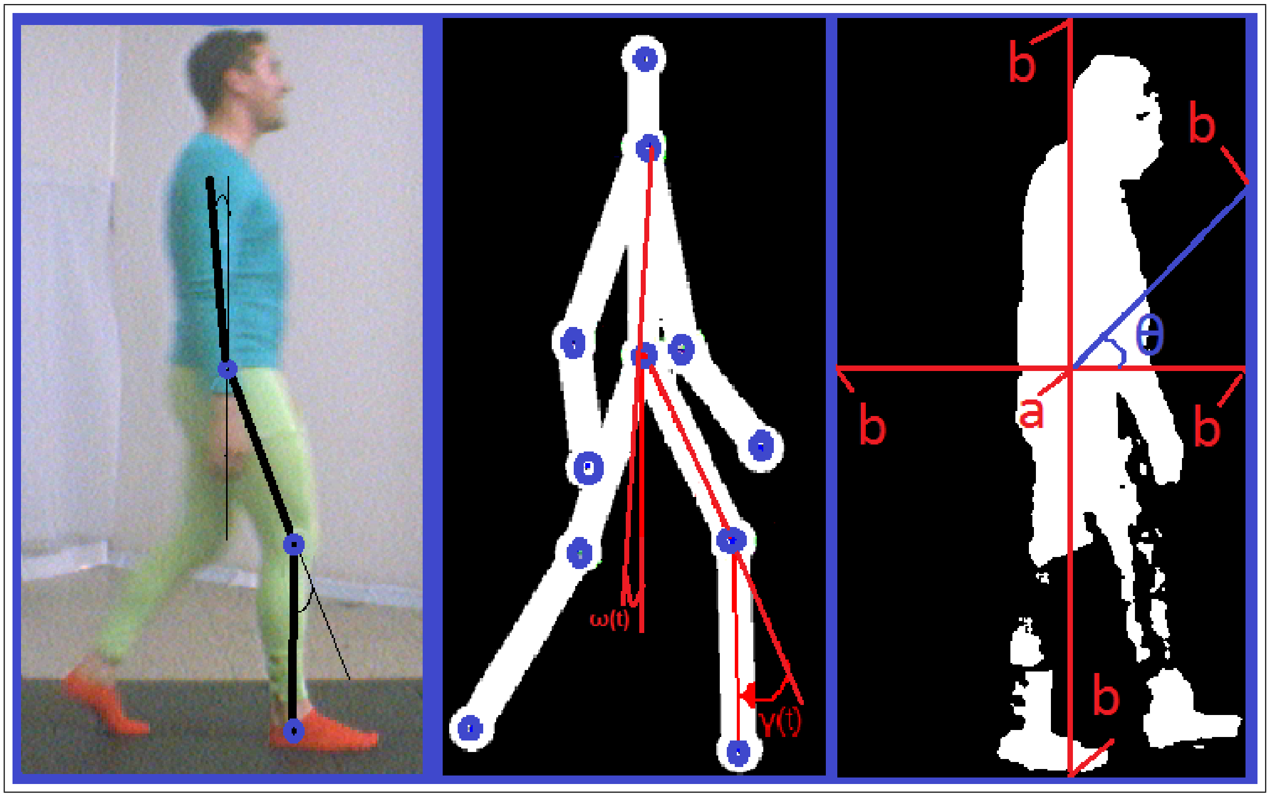


FIG. 2: Left: Angle patterns in a video Frame. Center: Pose associated to the current frame. Right: Centroid rerenced as a) while image Edge Points as b)

C. Assigning silhouettes to Poses: the prior

The set of poses, previously generated by a biomechanical gait model, was associated with a temporal sequence of human silhouettes, computed from a set of control and PD videos. A total of hundred poses describe well an entire gait cycle, i.e., at this temporal resolution changes were observable. At each time of the gait cycle, a pose is associated with the most similar silhouette of a training video-sequence, a task performed by an expert who assigned the mot probable pose for a particular gait phase and leg configuration. In general, video-sequences have a larger sampling frequency, that is to say, the number of video frames per second is larger than the number of poses generated by the biomechanical model. Therefore, a particular pose may be associated to a set of silhouettes and the expert simply picks the most similar. It is worthy to mention that such silhouettes are very alike among them since human gait movements can be considered as relatively slow with respect to the typical sampling frequency of a video, i.e., 30 fps. Yet this task was performed by an expert, it can be stated that for a given pose, any of the silhouettes associated to that pose might be considered as equivalent. Finally, the space of poses is composed of a succession of poses with their respective associated silhouettes.

D. Assigning Poses to video-sequences: the likelihood

Any gait video should then be described by a sequence of poses, a task accomplished by setting the most similar silhouette - from the space of silhouettes -to each frame of the video. The most similar pose is recovered by considering regional and geometrical metrics, regional by taking into account a degree of neighboring overlapping and geometrical by comparing a signature of the silhouette in a polar space. A more detailed description of the two metrics are presented hereafter:

1. A Regional Metrics for Comparing Silhouettes

The prior space of poses was built by assigning a single silhouette to each pose, a reference silhouette that stands for a statistical population of silhouettes. A main hypothesis is then that a set of captured silhouettes should maximally intersect the reference silhouette associated to a representative pose. For this reason, a bidirectional cost function is herein proposed for silhouettes to be compared, on the one side w.r.t every silhouette in the space of poses, but on the other side w.r.t the observed silhouette.

The cost function performs a per pixel p comparison between the silhouette obtained for each new frame A_t and the set of silhouettes B_i coupled to the pose $pose_i$. The silhouette metrics takes into account both the matching areas and the non-overlapping regions. For doing so, the silhouettes obtained from the video are firstly surrounded by a bounding box and then spatially aligned w.r.t the space-of-poses. A function Rt measures the per-pixel p non-overlapping area between silhouette A_t and the set of silhouettes B_i, i.e., the silhouette information exclusively contained in A_t as:

$$Rt = \sum_p M_A(p)(1 - M_B(p)) \tag{1}$$

Likewise, a function Bt per-pixel p calculates information solely in silhouettes B_i, as:

$$Bt = \sum_p M_B(p)(1 - M_A(p)) \quad (2)$$

And then a function Yt computes the overlapping between the two compared silhouettes as:

$$Yt = \sum_p (M_A(p))(M_B(p)) \quad (3)$$

Finally, a negative log likelihood is approximated [5] by:

$$g_s = -logp^d(M_A|M_B) \propto (a)\frac{Bt}{Bt + Yt} + (1 - a)\frac{Rt}{Rt + Yt} \quad (4)$$

The negative log likelihood stores the silhouette relationship between the non-overlapped (Bt or Yt) and the total shared area, including the overlapped zone (Yt). The parameter a is a coefficient that takes values between 0 and 1 and establishes the balance weight of the particular non-overlapping area, either silhouette A_t or B_i . Regarding this area comparison, in this approach two silhouettes sharing the same characteristics are compared but none of the associated silhouettes is preferred, either the one of the trained set or the non associated markerless video silhouette.

2. *Geometrical Silhouette Comparison*

A geometrical comparison is performed by mapping each silhouette to a polar space. For doing so and using the silhouette centroid as the reference, a line integral is computed every degree. This representation is defined as:

$$F(\Theta) = \int_C f ds; 0 \leq \Theta < 360 \quad (5)$$

Where $F(\theta)$ is the set of line integrals defined by a θ varying in the interval $[0, 360]$ with counter-clock-wise increments of one degree.

$$\int_C f ds = \int_a^b f(r(\theta))|r'(\theta)|d\theta \quad (6)$$

Each line integral is defined by equation 6. The integral requires an interval $[a, b]$ of the parameter r in a reference frame located at the centroid. The point a was set at the silhouette centroid and the b point was assigned to the edge of the box enclosing such silhouette. $r(\theta)$ represents the angle described by the line connecting the points a and b.

This representation allows us to obtain coarse-to-fine contour shape representations by changing the step θ. Each frame of a new sequence is then mapped to the space of poses. A Pearson correlation coefficient defines the degree of similarity between silhouettes as:

$$\rho(\theta) = \frac{\frac{1}{N}\sum_{i=1}^{N}(A_i - \bar{A})(B_i - \bar{B})}{S_a S_b} \tag{7}$$

where A_i and B_i are the polar-geometrical representation of the pose computed at frame t and the i-th pose in the space-of-poses, respectively. This Pearson correlation coefficient measures the degree to which two random variables vary together or to which they draw apart together, performing the concordance level of the polar shape representation.

Finally the most likely pose is obtained by fusing the two previously defined scores, namely the per-pixel overlapping and the geometrical polar comparison, as follows:

$$\Lambda = \alpha\rho(\theta) - (1-\alpha)g_s \tag{8}$$

where α is again a parameter between 0 and 1 that weights the metric.

E. Experimental Setup

The proposed approach was evaluated by quantifying the difference between a standard marker protocol, as ground truth, and two kinematic gait patterns, the knee and the hip temporal angular variations, obtained from the set of temporal poses selected with the proposed approach. The whole experimentation was carried out in a gait laboratory where sagittal videos captured from the left and right views, using IEEE cameras (320×240 and $30fps$), under semi-controlled illumination conditions. Each subject walked along a standard gait platform of $7.1m$ at least six times under both, marker and markerless conditions. In the marker protocol case, patients were recorded while walking with a set of 30 markers attached to the body, following the *plug in gait Vicon protocol* [10]. The markerless sequences were obtained with patients wearing a customized suit, as illustrated in Figure 2. For each recorded subject, at least two different gait cycles were considered.

The database collected for this work consisted in videos captured from 20 subjects, including 10 controls and 10 patients diagnosed with PD as follows; 5 of them were diagnosed

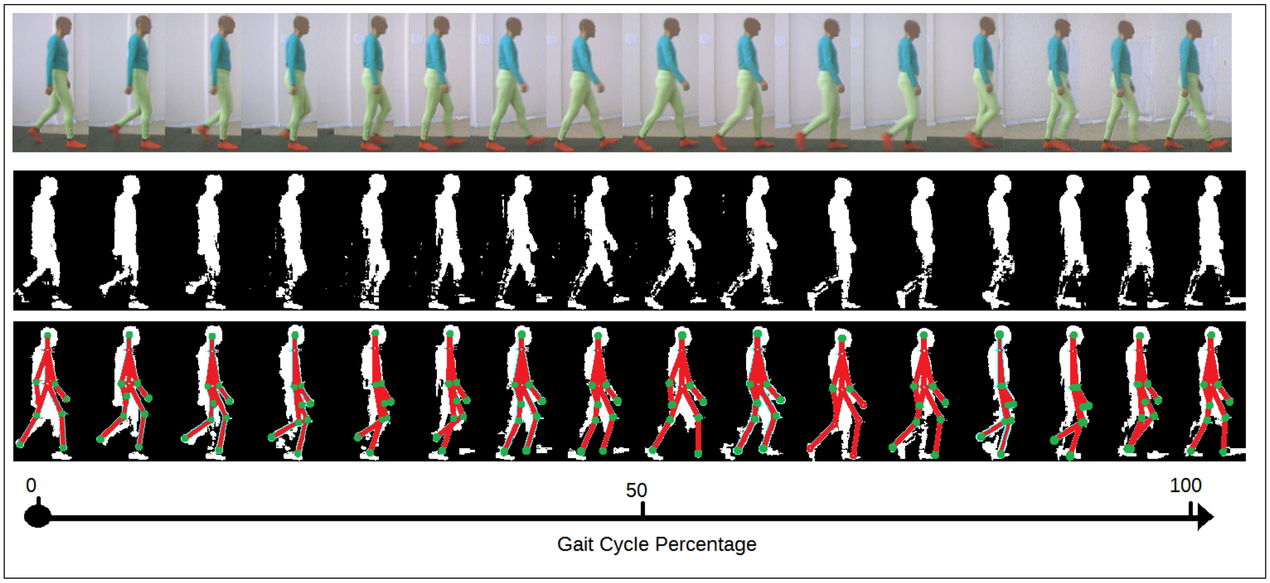


FIG. 3: Results of the pose recovery computed from a typical sequence of a control subject. Panel A) the raw video frames, B) the segmented video and C) the approach results

in stage 2 and 5 patients in stage 3. A total of 40 gait cycles were captured with an average of 18 frames per cycle. The ethics committee of the school of medicine at Universidad Nacional de Colombia approved the informed consent following the Declaration of Helsinki and each patient was informed about the procedure. The average age of the group of patients was $\sim$ 26 years for the normal set, $\sim$ 65 for the Parkinson's Disease stage II and III groups. Both groups, control and PD, were equally distributed by genre. The disease stage was determined according to Hoehn and Yahr scale by using the retropulsion test. The patients classified as stage 3 presented some balance impairment but they were Physically independent at the examination time.

III. EVALUATION AND RESULTS

The performance of the proposed approach was assessed by comparing the recovered gait patterns using the herein proposed markerless strategy w.r.t the gait patterns obtained by the conventional marker method, under a leave-one-out cross validation scheme, i.e., at each run, a different video-sequence was set aside for evaluation and the rest of video sequences, control and PD independently, were used to build the prior space of poses [Note2].

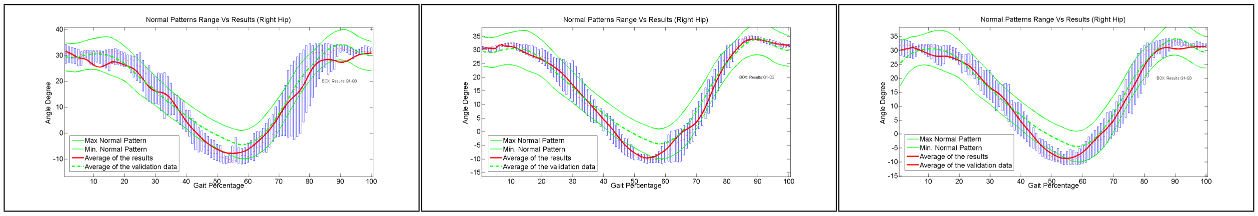
Figure 3 shows a typical pose recovery with the proposed approach (third row), obtained by computing a set of silhouettes (second row) for a gait video-sequence. As illustrated in Figure 3, even with a very blurred and incomplete silhouette segmentation, the similarity metrics are capable of setting an appropriate sequence of temporal poses to describe the dynamics of a complete gait cycle in a control subject. When a leg occludes the other, the corresponding recovered silhouette hardly matches the actual video silhouette, an effect produced by the multiple regional mismatches between the two silhouettes. Nevertheless, the proposed approach does succeed about capturing the global gait patterns such as the hip and knee flexion/extension during most of the cycle duration, achieving a reliable clinical estimation that in this case describes both the associated locomotion abnormality and the level of compromise.

A quantitative evaluation was carried out by comparing kinematic variables of interest, v.g. the flexion/extension motion for the knee or hip , during a complete gait cycle for both, the presented pose recovery strategy and the standard marker protocol. Firstly, for each group of study, the obtained kinematic patterns were plotted as a temporal series of statistical box-plots representing the whole gait cycle, being the average value the red line and the blue lower and upper boxes the spread of data among subjects (inter-quartile range). The dashed green lines show the normal distribution boundaries computed using the marker protocol, i.e., the ground truth [25].

Figure 4i illustrates the patterns obtained for the flexion-extension hip motion, during the full gait cycle for the three groups of subjects and different descriptors. Each column shows the obtained result for each of the evaluated descriptors, being (a) the regional descriptor, (b) the geometrical descriptor and (c) the integration of both descriptors. In the control group (top row), the top-left panel displays the biomechanical patterns obtained using the overlapping pose recovery. Notice in this case the strong correlation w.r.t. the normal patterns (green lines) during the whole gait cycle. Between the 70 % and 90 % of the cycle there is a more variability, likely associated to the force required when speeding up the motion for starting the limb swing. The top-middle panel presents the performance achieved by the geometrical descriptor and again, for most of the cycle the pattern is quite aligned with the expected normal model (green lines). However, at the beginning and end of the cycle, the temporal variance is almost null, an observation that might be attributed to the difficulty of capturing small changes between consecutive frames. Interestingly, when both descriptors (right panel) were combined, the results remarkably improved, the alignment was more precise and the variance was smaller in average.

Middle row of Figure 4i corresponds to the hip patterns obtained for the group of subjects with PD stage II. In general terms, a coherent description of the biomechanical patterns was accomplished since the obtained poses are usually within the interval defined by the model (boundaries green lines). However, the hip pattern recovered by the proposed approach shows an increasing variability among subjects, from about the 20 % to 40 % of the gait cycle, an observation probably related with the limitation of the physical model to generate poses that describe tremor patterns, the PD characteristic at early stages. It is however worthy to note that in terms of the disease this interval of the cycle, the limb swing, is associated to some control and stability loses. The trajectories captured by the overlapping descriptor (mid-left panel) show few variability and follow very close the PD patterns. Likewise, the geometrical descriptor (mid-mid panel) produces patterns that during most of the cycle are aligned within the control model, and unlike the previous descriptor, the resultant trajectories are more flexible and closely track the test patterns. Finally, when both descriptors are integrated (right panel), a much better performance is observed concerning the produced PD gait patterns, obtaining more flexible curves, with smaller variance and well aligned with the control gait patterns. Finally, the bottom row of figure 4i shows the computed hip patterns obtained for the group of subjects with PD stage III. At this advanced stage, patients present a strong tremor during the locomotion and in some patients even during the rest state. The disease at this degree is characterized by a high variability, i.e., the captured patterns depend on many factors such as the analyzed body hemisphere, the followed treatment, the level of rigidity and tremor states, among others. The recovered hip pattern using the overlapping method (left-bottom panel) follows the global trend of the ground truth patterns. Observe however that during a first part of the cycle ($0\,\% - 40\,\%$), the variability is quite increased, a finding that may be explained by the different stabilization each patient requires during the limb swing phase and the variable effort moments produced by the heel strike when the change to double stance is needed. The geometrical method (bottom-mid panel) achieves a more robust tracking with little variability, probably because this descriptor reduces the set of possible poses, i.e. results in a more sparse geometrical coding. Finally, the combination of both approaches result in a better description of PD patterns at this advanced stage of the disease.

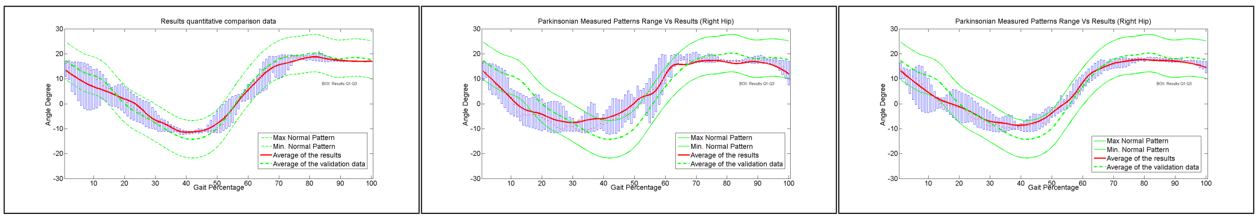
Figure 5i illustrates the flexo-extension knee patterns obtained for the different groups



(a) Hip results using regional silhouette comparison

(b) Hip results using geometrical sil. comparison

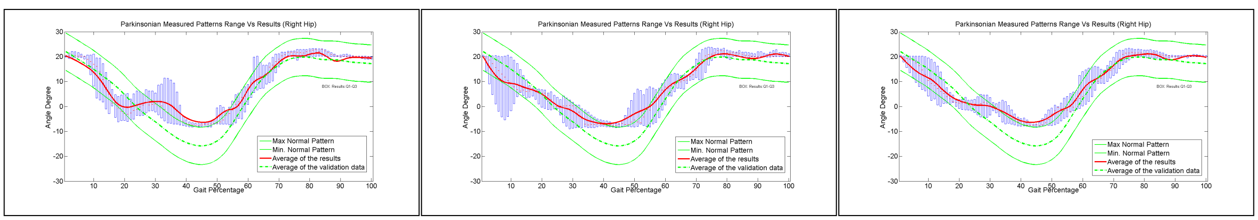
(c) Hip Results fusing a) and b), α=0.5



(d) Hip Results using region Silhouette Comparison

(e) Hip Results using geometrical sil. comparison

(f) Hip Results fusing d) and region e), α=0.5



(g) Hip Results using region Silhouette Comparison

(h) Hip Results using geometrical sil. comparison

(i) Hip Results fusing g) and h), α=0.5

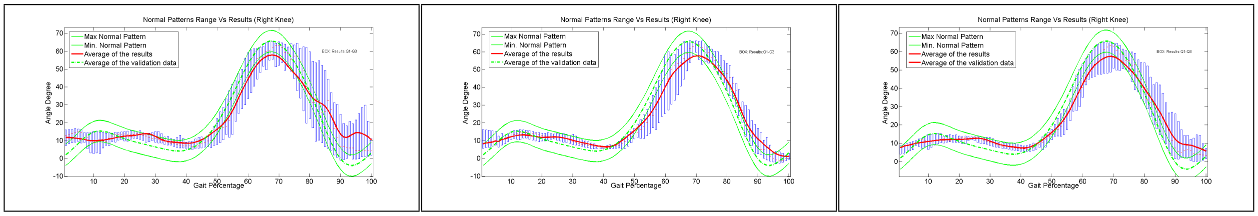
FIG. 4: Hip Results. Columns represent one metric for comparison, having Regional, Geometrical and Integrated metric from left to right, respectively. Rows are organized as follow: First Row for the Normal subjects results. Second Row for PD stage II patients. Third Row for PD stage III patients

of patients and different descriptors considered in the present study, namely, the left column corresponds to those patterns computed using the regional descriptor, the mid column shows the outcome computed with the geometrical descriptor and the right column reports the results obtained when both descriptors are integrated. The first row stands for the experimentation performed with control subjects. The top-left panel then shows the overlapping descriptor, evidencing how the pattern fits well within the boundaries established by the ground truth (green lines), with an increasing variability observed at the end of the cycle, likely because of the variable speeding up required for each patient to start the limb swing. The geometrical descriptor (top-mid panel) shows a strong correlation w.r.t. the ground truth patterns and only little differences are observed at the end of the cycle, probably because of the leg occlusion effect. The integration of both descriptors result in a quite perfect approximation to the knee-pattern.

The middle row of Figure 5i shows the computed patterns for the knee from patients with PD stage II, using the different descriptors, i.e., the overlapping, the geometrical and the integrated. In the mid-left panel, the overlapping descriptor coherently follows the normal pattern for almost every gait phase but showing certain stiffness of the average curve. Between the 30% to 50 % of the gait cycle, it is observed the larger inter subject variability, an effect that might be probably attributed to the heel strike effort developed by each patient to achieve stability. In contrast, the geometrical descriptor is more flexible at following the control pattern, even though a high variability of the evaluated patients makes the pattern exceeds the boundaries established by the marker protocol. Finally, the integration of both descriptors in column (c) achieves a a more precise description, even with the previously described stiffness at the beginning and end of the gait cycle.

Finally, the bottom row of Figure 5i reports the knee trajectories computed from patients at advanced PD stage, characterized by an important restriction of flexion movements that leads to stiffer gait cycle periods with a large inter-subject variability. As expected, the overlapping descriptor globally follows the knee pattern, but with a high variability because of the required increasing gait efforts to maintain stability, specially when changing to the double support and limb swing phases. As in previous cases, the geometrical descriptor tracks better the different gait phases. This descriptor is well associated with poses during the gait cycle, highlighting some of the main poses that result fundamental to follow knee-patterns. The integration of both descriptors again shows a better representation of trajectories, with a natural shift phase produced by the pose prediction model, patterns globally obtained even during the occlusion phases of one leg with respect to the other.

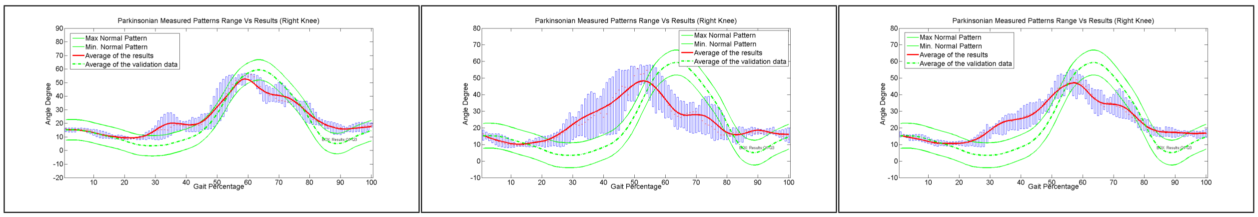
Secondly, a global quantitative analysis was carried out by measuring the degree of statistical dependence between the computed mean trajectories (red lines) and the established ground truth (mean green lines), using the Pearson Correlation Coefficient (PCC) and the root mean square error (RMSE). The PCC measures the degree to which two estimated kinematic patterns vary together or to which two patterns draw apart. This PCC evaluation is specially important in gait analysis since it establishes a quantitative relationship



(a) Knee results regional silhouette comparison

(b) Knee results using geometrical sil. comparison

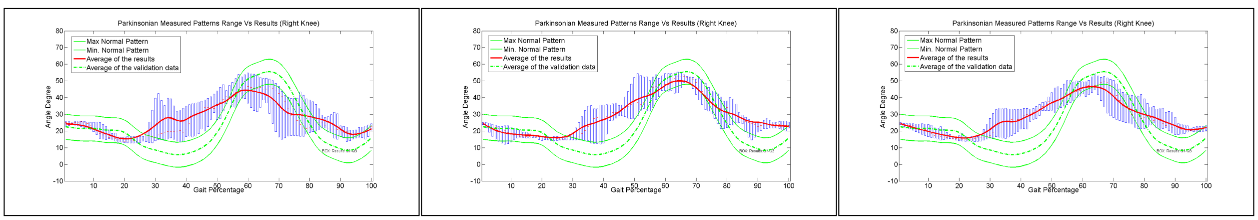
(c) Knee results fusing a) and b), α=0.5



(d) Knee Results using region silhouette comparison

(e) Knee Results using geometrical sil. comparison

(f) Knee Results fusing d) and e). α=0.5



(g) Knee Results using region silhouette comparison

(h) Knee Results using geometrical sil. comparison

(i) Knee Results fusing g) and h), α =0.5

FIG. 5: Knee Results. Columns represent one metric for comparison, having Regional, Geometrical and Integrated metric from left to right, respectively. Rows are organized as follow: First Row for the Normal subjects results. Second Row for PD stage II patients. Third Row for PD stage III patients

between an estimated kinematic variable and a particular pathological pattern. The correlation is calculated then between the average of the marker protocol measurements (green trajectories) and the mean of the obtained patterns for the whole group of patients (red lines). On the other hand, the RMSE is commonly used to measure the local differences between two signals, allowing us to measure the level of error in particular intervals of the gait cycle.

Table I summarizes the PCC and RMSE indexes obtained for both descriptors as well as for the integration of them. In general terms, the PCC and RMSE show the close relationship evidenced in the previous analysis, between the computed patterns and the ground truth. In average, the descriptor configurations achieve an averaged PCC of 97.3, suggesting a good match between the mean trajectories. In RMSE terms, which accounts for the local variation w.r.t the ground patterns, a maximum local error of 2.93 degrees was obtained for the hip and 7.5 degrees for the knee, figures that can meet clinic requirements in actual scenarios. The fusion of global and local representations in all cases allows a better correlation w.r.t. ground patterns and also a reduction of the local error.

For the trajectories computed for PD stage II population, Table II shows the performance obtained in terms of the PCC and RMSE. Despite these trajectories present much more variations, probably because the aforementioned typical tremor during gait, an average correlation of 0.86 is observed for all patterns, being the overlapping descriptor more effective for following the kinematic patterns. Interestingly, the global correlation is better for the overlapping descriptor than for the integrated one, probably because of the recurrent local variation introduced by the geometrical trajectories along the gait cycle. Again, the three biomechanic markerless descriptions can be included as part of an evaluation clinical protocol.

Finally, table III presents the PCC and RMSE for the trajectories computed for patients with PD at stage III. The geometrical descriptor achieves a better representation of these pathological trajectories, with and average of 0.88 and 8.15 in PCC and RMSE, respectively. The integration of both descriptors also allows the stabilization of the pose prediction and therefore a proper correlation for the biomechanic patterns, reporting in average a CPP of 0.87 and RMSE of 8.3.

TABLE I: Quantitative Results for Geometrical, Overlapping Silhouette comparison and Integrating both:Normal walks

	Geometrical		Regional		Integrated, α=0.5	
Joint Angle	PCC	RMSE	PCC	RMSE	PCC	RMSE
Right Hip	0.99	2.9	0.98	3.2	0.99	2.7
Right Knee	0.96	6.6	0.95	7.9	0.97	7.0

TABLE II: Quantitative Results for Geometrical, Overlapping Silhouette comparison and Integrating both:Parkinson Stage II

	Overlapping		Geometrical		Integrated, α=0.5	
Joint Angle	PCC	RMSE	PCC	RMSE	PCC	RMSE
Right Hip	0.99	2.27	0.9	5.66	0.97	3.67
Right Knee	0.94	7.91	0.54	15.75	0.82	11.6

TABLE III: Quantitative Results for Geometrical, Overlapping Silhouette comparison and Integrating both:Parkinson Stage III

	Overlapping		Geometrical		Integrated,α=0.5	
Joint Angle	PCC	RMSE	PCC	RMSE	PCC	RMSE
Right Hip	0.95	5.48	0.96	4.94	0.97	5.0
Right Knee	0.71	12.2	0.8	11.35	0.77	11.6

IV. DISCUSSION

This work has presented a markerless approach capable of recovering the most probable pose associated to actual gait sequences. The method performs an objective assessment of the biomechanic gait patterns in control and Parkinson patients at stages II and III. The proposed approach starts by computing a set of silhouettes, representing the patient gait observations from an ordinary video-sequence, which are coded by using regional and global descriptions that highlight relevant shape features at each video sequence time. These coarse characteristics are mapped to a space of poses, generated by a biomechanic model, where the metrics matches the most likely pose associated to a particular moment of the gait cycle. Temporal matched poses produced the biomechanics for the knee and the hip, from which flexion/extension patterns are estimated. The proposed markerless approach follows control and Parkinsonian gaits even under noisy conditions, i.e., occluded legs or silhouettes contaminated with background noise. In average the proposed approach achieved a PCC of

0.90 for the whole cycle and group of subjects considered, demonstrating the potentiality of this tool for quantitatively support the expert diagnostic.

Gait analysis is typically carried out by using marker strategies, for which a set of reference points are tracked during a gait sequence while biomechanic correspondences are set by integrating the marker trajectories. Afterward, the patient trajectories are compared with typical gold standard patterns that help the physician to support a particular diagnosis or clinic decision. This method is however limited by the fixed relationships between the markers and the requirement that each marker must be properly localized upon a particular bone prominence. Overall, this method is invasive since the patient gait is captured under controlled conditions, with custom devices attached to the body, preventing the natural gait gesture. Particularly, the subtle differences among several disease stages are hardly detected and become therefore highly dependent on the physician expertise. Currently, markerless strategies have emerged as a potential solution to precisely track and determine motion patterns by exclusively using video-sequences. In general, these strategies code spatio-temporal video-descriptors with local, regional or global features, facilitating a further analysis of hidden kinematic patterns. On the one hand, markerless methods based on local features compute salient time-space blocks, resulting in a dynamic description from the video, independently of any geometrical dependency [1]. These strategies are flexible and characterize different kinds of motions but at the cost of losing spatial relationships, which are fundamental in case of gait analysis. On the other hand, global approaches are focused on the spatio-temporal characterization of the object shape. These approaches overcome the occlusion problems appeared when using classical tracking strategies, but many times they admit non-natural human poses because of their flexibility to describe deformed objects. This feature results restrictive for a biomechanic analysis since in this case it is always important a careful pose characterization.

In the proposed approach, the integration of a physical prior model allows the presented strategy to track normal and pathological gaits by matching poses along the time. This structural gait representation is fully correlated w.r.t the energy consumption pattern described for different gait types and locomotion abnormalities. This physical model generates a set of spatio-temporal poses constrained by the energy efficiency of the produced pattern. This set of poses with certain gait variability allows the method to associate the silhouettes to different Parkinson's disease stages, but avoiding non-natural body configurations, for instance, a set of poses that describes a complete rotation of the knee, i.e. a free rotation of 360^o.

On the other hand, gait observations are captured by using a background/foreground detection, robust to illumination changes and computationally efficient. Every estimated silhouette is characterized by using regional and global shape descriptors. These descriptors are used to search the most probable poses by the learned model and to match current video-sequences. The sequence of recovered poses permits to measure kinematic variables that can be used to analyze the gait. Additionally, the herein proposed strategy opens up the possibility to carry out further analysis about the dynamic silhouette changes along the time without the restriction of locating specific prominent points.

The proposed approach tracks abnormal locomotion patterns, such as parkinsonian movements in middle and advanced stages of the disease, even superimposed with tremor state patterns. Some difficulties are present when the legs are occluded because the shape descriptors could be ambiguous and several poses can be retrieved from the learned space. However, a causal pose restriction might overcome this limitation by following to temporal history of previous predicted poses. Likewise, when some types of gaits present large periods of resting state, corresponding to very advanced stages of the PD, the choice of poses may be mislead, but these abnormal patterns might be detected by the model by accounting for long periods of minimal temporal variance. Additionally, the method could be enriched by using more sophisticated skeletal methods but at the price of introducing many control variables, impractical in a clinical scenario. Likewise, this method could be easily adapted to other gait pathologies with some sort of muskulo-skeletal deficiency, for instance in case of diplegic gait, associated with spastic cerebral palsy, approximated by restricting the spring-mass system of the physical model.

V. CONCLUSIONS

This work has introduced a novel markerless strategy that computes biomechanical patterns of control and parkinsonian patients. The approach associates artificial poses generated by a physical model with noisy observations computed from video-sequences. The method was successfully assessed in a population of patients diagnosed with Parkinson disease at stage II and III. In general, the method matches the biomechanical patterns even for advanced stages of the disease and even tough Parkinson's disease diagnosis relies highly on each expert knowledge also it was observed high intra-variability, particularly in the upper body, in the analyzed stages. Future works include the analysis of other gait pathologies and the extension of multi-view tracking to compute 3D biomechanical patterns.

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[Note1] Note1. There exist several marker protocols such as Plug-in Gait (PiGVicon Motion Systems, Oxford, UK), SAFLo (Servizio di Analisi della Funzione Locomotoria), LAMB, among others: Ferrari et al; Quantitative comparison of five current protocols in gait analysis; Gait Posture; 2008.

[Note2] Note2. a sequence of artificial poses computed from the physical model and associated to silhouettes of the training video-sequence, spanning a complete gait cycle.

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4 Conclusions

- This thesis integrated kinematics patterns with markerless video silhouettes, the video data recorded at UN Laboratory was divided into normal and pathological gait motions, the proposed methodology was tested separately and the results followed the angle patterns behavior through a gait cycle, particularly it was obtained better performance in the normal control subject's motion, the correlation between the recovered poses for Parkinson's dissease and measured angle patterns may be considered as an indicator that the method follows up flexo-extension of hip and knee joints.

- The proposed methodology locate successfully the lower limbs in markerless gait analysis with a Pearson correlation coefficient higher than 0.95 for normal gaits and 0.70 for pathological gait motion, the geometrical comparison algorithm reach higher correlation in normal gaits, this due to the fact that is invariant to translation, for that reason the matching among silhouettes is not a fundamental step. Compared with reviewed methods, this projects integrate data from kinematics to enhance an indirect measurement method, usually two separate fields in biomechanics.

- Although the work was focused on lower limbs the methodology may be expanded to other patterns, such as upper body limbs, and to different views. It is precisely the upper limbs spatio-temporal information one important difference in the two sets of data: Normal and pathological. Analyzing the normal subjects' gaits this parameters may be considered uniform and similar in the cycles recorded, while in the Parkinson's dissease patients upper limbs exhibited irregular movement, having different levels of rigidity in one or both sides of the body, ane even sometimes the variability was observed in the same patient.

- There is also a possibility to use ofthe same methodology in other type of motion, that would require the use either a biomechanical model or directly measured kinematics to obtain the prior information for the Map of Poses, of the other pathologies or specified actions, such as Sport Gestures; one important field that may be explored. Then, this project is not static nor it is already delimited, indeed it is clean canvas that may continue exploring human motion as a tool with a high potential.

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