REGIONAL KINEMATIC CHARACTERIZATION OF MOTION TRAJECTORIES TO CLASSIFY GAIT PATTERNS

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Undergraduate thesis to apply for a degree in electronic engineering

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RESUMEN

Título: Caracterización cinemática regional de trayectorias de movimiento para clasificar patrones de marcha [1]

Autor:
Luis Carlos Guayacán Chaparro[2]

Palabras Clave: Análisis de marcha sin marcadores, Trayectorias de movimiento, Análisis regional de movimiento.

Descipción

El análisis cinemático de la marcha es fundamental en el diagnóstico, tratamiento e implementación de métodos de rehabilitación en patologías asociadas con el movimiento. Este análisis se desarrolla principalmente a partir de la descripción cuantitativa de los desplazamientos de los diferentes segmentos del cuerpo. En la rutina clínica, la cuantificación de estas variaciones se realiza típicamente a través del seguimiento de un conjunto de marcadores ubicados en prominencias óseas, que estiman la cinemática general de la estructura musculo-esquelética. Sin embargo, la cuantificación basada en marcadores se realiza utilizando estrictos protocolos de captura, lo que limita el gesto natural de la marcha y la exploración de variables dinámicas que podrían ser altamente descriptivas en ciertas patologías. Este trabajo presenta un descriptor de movimiento regional que permite la cuantificación de las marchas normales y parkinsonianas. La metodología propuesta inicia calculando un conjunto de trayectorias que describe el movimiento de los principales articuladores durante la marcha. Estas trayectorias son agrupadas regionalmente según similitudes espaciales y cinemáticas. Las trayectorias agrupadas en cada región son caracterizadas utilizando un descriptor espacial de movimiento y una tabla de ocurrencia de velocidades. El descriptor es finalmente codificado en una bolsa de palabras y mapeado a una máquina de soporte vectorial para obtener una predicción de la marcha analizada. El método propuesto fue evaluado en un conjunto de 84 videos de la marcha de 7 pacientes control y 7 pacientes diagnosticados con parkinson, obteniendo una exactitud en la clasificación del 92,86%.

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[1] Trabajo de Grado

[2] Facultad de Ingenierías Físico-Mecánicas. Escuela de Ingenierías Eléctrica, Electrónica y de Telecomunicaciones. Director: Fabio Martinez Carrillo, PhD. Codirector: Said David Pertuz Arroyo, PhD.

ABSTRACT

Títle: Regional Kinematic characterization of motion trajectories to classify gait patterns. [1]

Author:
Luis Carlos Guayacán Chaparro[2]

Key Words: Markerless Gait analysis, Motion trajectories, Regional motion analysis.

Description

Gait kinematic analysis is fundamental diagnosis support, treatment, monitoring and implementation of rehabilitation methods in pathologies associated with movement. This analysis is mainly developed from quantitative and qualitative description of displacements of the different body segments. In clinical routine, the quantification of these variations is typically done through the monitoring of a set of markers located in bony prominences, which allow to estimate the global musculoskeletal kinematic. Nevertheless, markers-based analysis is carried out in controlled environments, using strict capture protocols, which limits the natural gesture of walking and the exploration of dynamic variables that could be highly descriptive for certain pathologies.This work presents a regional motion descriptor that allows the analysis and quantification of normal and parkinsonian gaits. The proposed method starts by computing a set of salient trajectories that describe the motion of main articulators during gait. Such trajectories are then regionally grouped following spatial an first-kinematic order similarities. Each trajectory group is fully characterized by using a spatial motion descriptor together with a occurrence velocity databoard. Finally, the implemented descriptor is coded in a bag-of-features and mapped to a support vector machine model. This methodology is able to predict normal and pathological gaits. The proposed method was evaluated from a set of 84 gait videos of a total of 7 control patients and 7 parkinsonian patients, obtaining an accuracy of 92,86%.

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[1] Bachelor Thesis

[2] Facultad de Ingenierías Físico-Mecánicas. Escuela de Ingenierías Eléctrica, Electrónica y de Telecomunicaciones. Advisor: Fabio Martinez Carrillo, PhD. Co-Advisor: Said David Pertuz Arroyo, PhD.

INTRODUCTION

Human gait is a complex and efficient process that includes the interaction of muscles, bone structure and neuromuscular commands [12]. While normal gaits are described as optimal synchronization of all related elements [1], pathologies associated with movement are summarized as deficiency in bipedal displacement because the limitations in any of implied components [15] [32]. Gait kinematic analysis allows to characterize pathologies associated with movement. by the description and the correlation of spatio-temporal variation of body segments, the center of mass and the joints during locomotion. In clinical practice, marker-based analysis are typically implemented to analyze such spatio-temporal variations by tracking external devices attached to the body in special zone of interest [9]. However, in literature has widely demonstrated that such analysis limits the natural gesture of walking and limits this complex analysis to a set of reduced tracking points [6, 9, 20, 28].

Recently, developments in video processing and pattern quantification have allowed to propose novel strategies that quantify gait dynamic by using exclusively video information. For instance, geometric descriptors [17], tracking of salient features are combined with machine learning models [20] and deep sensors [18] to describe the complex process of locomotion. Such approaches allows the natural gesture representation as well as the exploration of new regional patterns that could be associated to different pathologies. Nevertheless, these methods have shown some limitations, such as sensitivity to occlusion of body segments, and problems w.r.t abrupt changes in scene appearance and perspective. Some of these challenges has been treated in other research areas, such as animation [10], video surveillance [8], recognition of activities [30], but with remaining limitations in the representation of gestures and local patterns that could define abnormal behaviors.

This work presents the following main contributions:

- 1. The capture of a complete markerless dataset composed of 84 videos, belonging to 42 sequences of 7 parkinson's disease patients and 42 sequences of 7 control patients under semi-controlled conditions. These sequences were taken over the same background with a static camera that allows to focus strategies on automatic classification between control and abnormal patterns.
- 2. A regional gait characterization from motion trajectories that are directly related with body segments. Such trajectories are grouped by spatial and kinematic similarities by using a correlation matrix and a k-means clustering. Such representation allows a local analysis of different kinematic gait patterns.
- 3. A Motion characterization of regional segments by using, on the one hand, a spatial motion pattern (SMP) combined with optical flow information which here is introduced as spatial kinematic pattern (SKP), and on the other hand, a dartboard formed with simple coding the velocity information into a semi-circular grid. The SKP was built from three different maps: flow orientation, flow magnitude and intensity, respectively. The semi-circular dartboard was designed to be invariant to gait direction and robust to large changes in direction.

The rest of the document is organized as follow: in chapter 1 is presented a review of gait analysis and Parkinson's disease. In chapter 2 the objectives of this research are listed. In chapter 3 the proposed approach is introduced. The details of the captured dataset are reported in chapter 4. Then, evaluation and results are presented in chapter 5. Finally, conclusions are presented in chapter 6.

Chapter 1

GAIT ANALYSIS AND PARKINSON'S DISEASE

1.1 CLINICAL GAIT ANALYSIS

Kinematic gait analysis is a fundamental tool to support diagnostic tasks, treatment, monitoring and implementation of rehabilitation methods in pathologies associated with movement. In general terms, this analysis is based on description and quantification of body segment movements, the variation of the centers of rotation in the joints and the monitoring of global dynamic described by the center of mass. Such characterization is then fundamental to quantify movement patterns and to define pathological movements from large variations with respect to control ranges. From such information it is possible to obtain different relationships of variables over time, which are presented to the expert as a clinical report to support the diagnosis. Additionally, using such characterization it is possible to track the progress or setback on their rehabilitation [2] [11].

In clinical practice, kinematic analysis together with kinetic and energy consumption variables are integrated to reach the clinical report. In terms of kinematic analysis, the temporal description of the displacement is quantified using a set of markers (active based on leds and passives using reflective materials) that follow points of interest during the movement and allow to relate different body segments. However, this methodology limits the description of the movement and simplifies the body structure during the displacement to a few motion trajectories. In addition, markers are devices that alter the gait gesture and prevent a faithful capture of the patient's movement [6] [20] . On the other hand, the gait recording in enclosed environments, with particular clothing and restricted capture protocols, prevents typical and free movement of patients (see figure 1). Likewise, the implementation of such protocols requires clinical and technical specialized training of personnel.

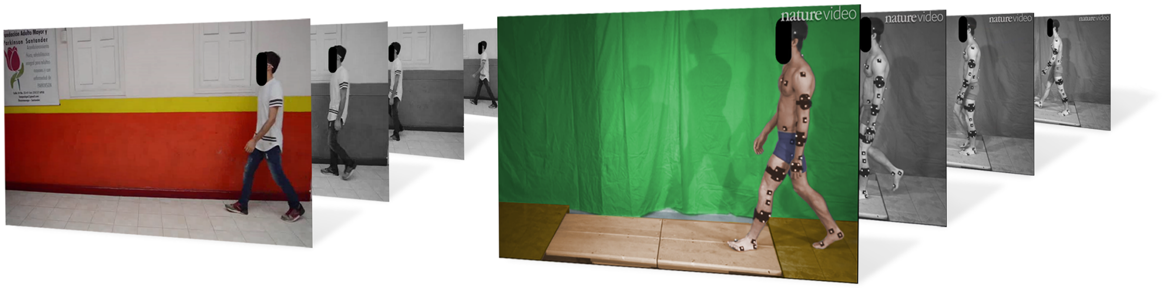

Figure 1: Comparison between markerless and marker based gait analysis. Left: a markerless gait capture with casual clothes allowing a natural gait. Right: A gait captured with specific clothes and with around 40 markers on the body which can lead to unnatural movements [29].

1.2 MARKERLESS GAIT ANALYSIS

Recently, areas such as computer vision and machine learning, have allowed to characterize complex patterns captured in video sequences with minimal restrictions [24]. These technologies have been developed for different uses such as animation [10], video surveillance [8], and rehabilitation [19], among others. These techniques, commonly called analysis without markers, characterize certain spatio-temporal behaviors in the video sequences, which are associated with particular displacements that define the semantics of a movement. In terms of rehabilitation, the characterizations of these patterns can be associated to types of control and pathological gaits, and at the same time, allow to make inverse analyzes on the new patterns found, with respect to a particular gait of study. In the literature, some studies involving different areas of knowledge have been reported, such as: computer vision, pattern analysis and machine learning, which seek the development of new clinical tools that allow a technological and systematic support to the analysis of gait.

In [17] a seminal work was proposed for the automatic classification of patients describing different types of gait, normally classified as: gaits with musculoskeletal disorders, parkinsonian and control gaits. In this work the silhouette of the person was automatically captured in each frame of the video and then a geometric descriptor was developed on the sequence of the silhouettes that allowed to train a vector support machine. This strategy, however, presents limitations of representation in controlled environments. In [19] gaits captured in more complex environments were included, so the authors integrated movement descriptors, as well as movement appearance characteristics to automatically classify normal and pathological gaits. In [20] a method based on the hidden Markov chains (HMM) was proposed to calculate trajectories of movement of the different segments of the body, while the displacement was developed. Additionally, this approach uses neural networks to classify different types of gaits. This approach is dependent on the continuous and precise calculation of the trajectories corresponding to the movement, which can be a limitation in terms of occlusion.

Other works such as those reported in [3] and [26] have focused on the classic use of gait variables and their subsequent analysis using machine learning tools, such as vector support machines for automatic recognition and classification tasks. These tools are fundamental for diagnostic support, but they are still limited by the classic variables and based on markers used for recognition. Additional strategies are based on the capture of movement using new sensors, such as the kinect cameras [27] and [18]. These sensors complement the information of traditional cameras (RGB) with depth information, which implies more analysis precise movement in three dimensions, but with a space restriction due to the depth reach of these cameras.

Currently there is a wide range of works that include the recognition and detection of movement patterns in video. These works have been focused generally for the detection and recognition of activities, but their use can, in some cases, be extended to the biomedical field to understand the progress from new correlations and temporal space patterns, as product of the video analysis. For example, in [31] they use a statistical analysis of the forms to obtain digital signatures of the gait in applications of biometric identification. Also, in [16] and [23] a set of orthogonal moments and geometric descriptors is used to characterize the temporal sequence of the body segments in applications of biometric gait recognition.

In [30] a descriptor was proposed for the recognition of activities based on trajectories of movement. In this work, a local descriptor that contains information of appearance and apparent movement is calculated around each trajectory. These descriptors are quantified using a bag of words, resulting in a histogram of occurrence as descriptor of each video. In [4] is presented a technique for the segmentation of video images based on the grouping of trajectories, which proves to be robust against occlusions. Finally, in [25] a strategy is proposed for the analysis of the activities based on the local grouping of trajectories that allows to classify the activities and to recognize the spatio-temporal location where it is developed. The multiple strategies developed in the recognition of actions and modeling of the movement in computer vision represent a starting point for the study and characterization of gaits in uncontrolled environments and without the use of invasive external elements that alter the natural gesture of movement.

1.3 PARKINSON'S DISEASE

This work was focused on the analysis of parkinson's gait, taking into account the interests of the research group which the author belongs to. Parkinson's disease (PD) is, worldwide, the second most common neurodegenerative disorder, surpassed only by Alzheimer's disease. PD is characterized by the progressive death of selected neuron populations, especially the dopaminergic neurons, located within the substantia nigra pars compacta. This causes a loss of dopamine, which generates a series of motor disabilities characteristic of PD.

PD rarely occurs in people younger than 40 years, whereas that its prevalence is estimated at 1% for the population over the age of 60. Males are more often affected than females. After an average of 5 years of disease, most of patients also develop non-motor symptoms, among them: cognitive decline, depression and autonomic failure as well as pain and sensory symptoms. After 15 years from diagnosis, more than 70% of patients would have died and about half of those surviving, require nursing-home care [5]. In 2015, PD affected 6.2 million people and resulted in about 117,400 deaths globally [13].

1.3.1 Diagnose and Follow up of the Parkinson's Disease.

In the clinical praxis, diagnosis and assessment of the advance of PD can be difficult, especially for the early stages. No specific test exists to diagnose Parkinson's disease. The medical professional trained in nervous system conditions (neurologist) will diagnose Parkinson's disease based on the medical history, a review of the signs and symptoms, and a neurological and physical examination. Physician may suggest a specific single-photon emission computerized tomography SPECT scan called a dopamine transporter (DAT) scan. Although this can help support the suspicion that the patient has Parkinson's disease, it is the symptoms and neurological examination that ultimately determine the correct diagnosis.

1.3.2 Characteristic Gait Patterns of The Parkinson's Disease.

Amongst its other clinical features, it includes a shuffling gait (see figure 2). This gait is characterized by [21]:

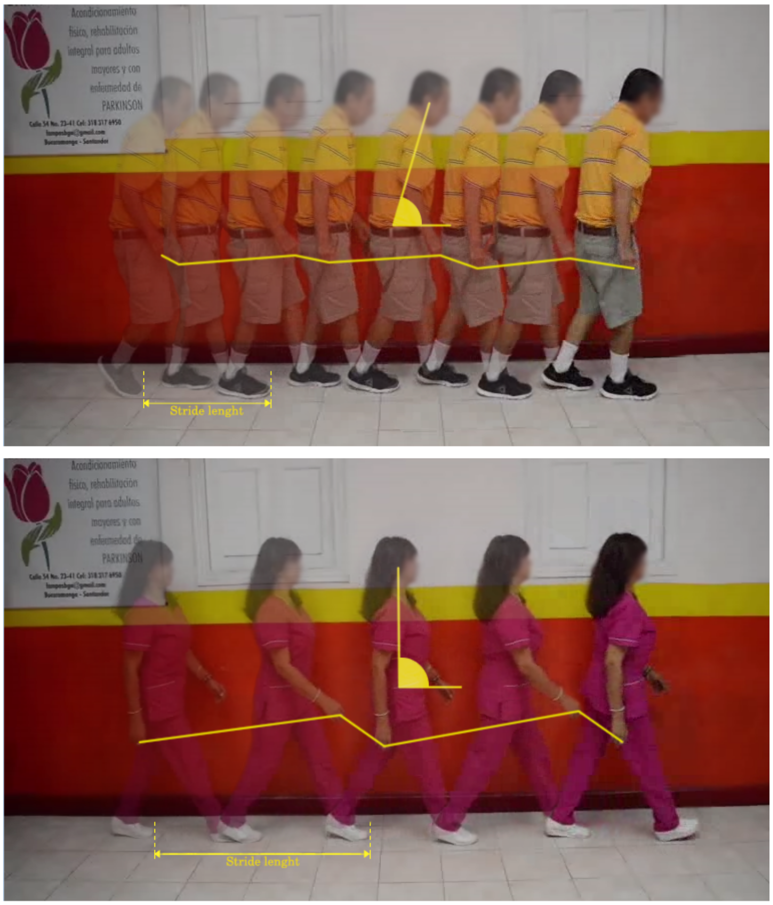

Figure 2: Some affected gait gestures. Stooped posture, reduction of the swing of the arms and a shorter straight length of the parkinsonian gait (top) are compared with a control gait (bottom).

- Reduced or absent arm swing.
- Reduced trunk rotation.
- A forward stooped posture which decreases low back curve or forward lean of the head or whole body, making the patient looks hunched over.
- Reduced amplitude of motion at the hips, knees and ankles.
- Reduced footstep size and decreased ground clearance.

Chapter 2
PROPOSED METHOD

A markerless strategy is herein introduced to code hierarchically motion patterns and automatically classify pathological and control gaits. The method starts by computing long motion trajectories that densely represent gait in video sequences. Such motion trajectories are computed at pixel level and allows to code local kinematic descriptors. Around each trajectory were computed spatial kinematic pattern (SKP) from appearance, and speed and angle of the underlying flow combined with velocity information of each trajectory. The local descriptors are used as input into a regional clustering scheme. The resulting clusters are coded as occurrence of SKP and allow a regional analysis of different body segments during locomotion. From individual regions as well as the combination of the regions is possible to obtain video gait descriptors that are mapped to a support vector machine to obtain a prediction. A description of each of these steps, will be described in following subsections.

2.1 LONG MOTION TRAJECTORIES

The computation of motion descriptors based on apparent velocity flow field has been successfully applied in different context to recognize general objects and action with strong kinematic and postural differences. These descriptors are however limited to first kinematic order description, since optical flow field is namely computed among pair of frames. From such assumption, the patterns captured are in general localized and smooth. In gait analysis such coarse velocity field characterization could be insufficient to differentiate among control and pathological patterns, especially in early stages of disease. To overcome such limitations, a set of dense long trajectories were herein implemented to characterize gait in video sequences [30]. These trajectories are local motion

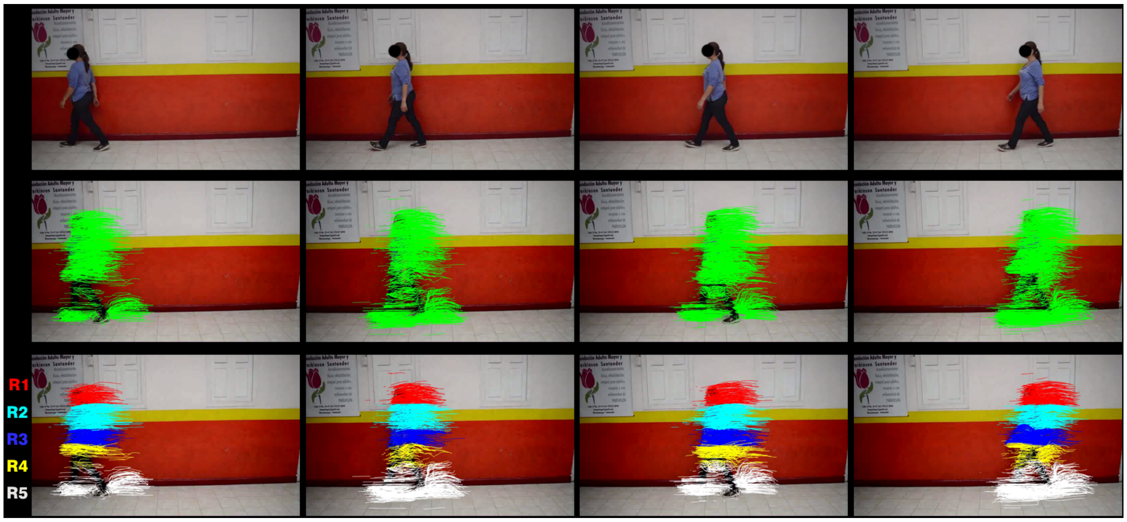

Figure 1: A visualization of trajectories and clusters of a video sequence. First row: video sequence of a typical gait. Second row: long trajectories computed along locomotion. Third row: trajectories clustering where can be observed how each computed region approximates a body segment throughout the video.

primitives based on tracking salient points along the video sequence, allowing a salient representation of gait gestures. The trajectories computation starts by computing the Farneback dense flow based on polynomial expansion [14]. In this method a neighborhood of each image pixel is approximated by quadratic polynomial expression, defined as: $f(x) \sim \mathbf{x}^T\mathbf{A}\mathbf{x} + \mathbf{b}^T + c,$, where $\mathbf{x} = (x, y)^T$ are pixels, $\mathbf{A}$ are unknown coefficient of representation with some bias b. Then, the d field displacement is obtained as the difference of quadratic coefficients in consecutive frames, as: $d = -\frac{1}{2}A_1^{-1}(b_2 - b_1)$. This algorithm presents a good compromise between accuracy and speed.

Hence the computed dense flow is temporally smoothed by using a median filter over the displacement information. For doing so, feature points $P_t = (x_t, y_t)$ are sampled on a regular grid and tracked in time t at different spatial scales. The median filtering tracking w.r.t the dense optical flow field $w = (u_t, v_t)$, can be expressed as: $P_{t+1} = (x_{t+1}, y_{t+1}) = (x_t, y_t) + (M * w)\,|_{(\overline{x}_t, \overline{y}_t)}$, where M is the median filtering kernel, and $(\overline{x}_t, \overline{y}_t)$ is the rounded position of (x_t, y_t). The followed points are concatenated to form a trajectory $(P_t, P_{t+1}, P_{t+2}, \ldots, P_{t+n})$. Some trajectories with strong deviation displacement as well as relative static trajectories are removed from analysis. An example of computed trajectories during a typical gait is illustrated in Figure 1.

2.2 DESCRIPTOR

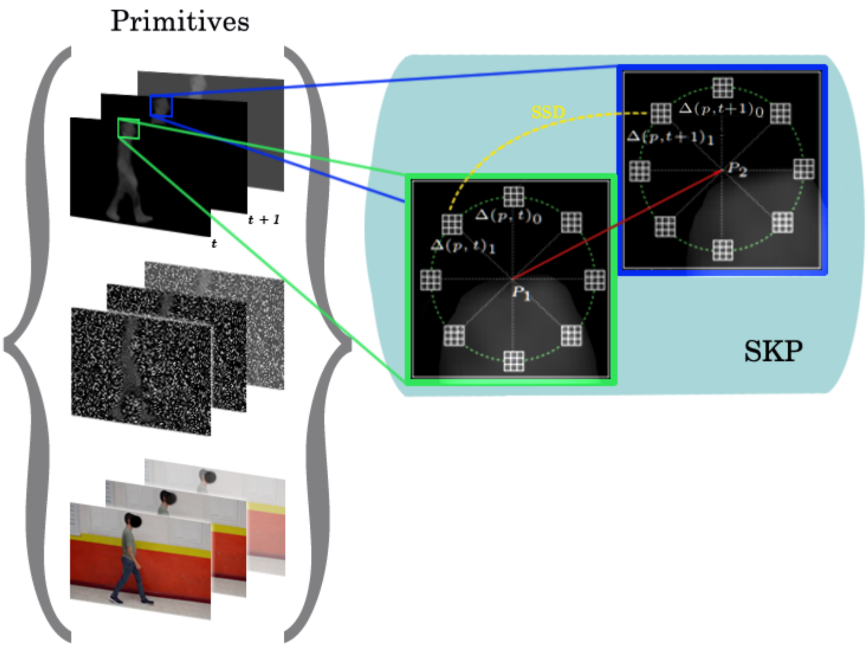

Figure 2: A set of video primitives were herein considered to compute the local SKP descriptor. Such primitives correspond to intensity, speed and orientation of the velocity field. Locally among consecutive frames is computed the SKP along motion trajectories.

2.2.1 Spatial Kinematic Patterns (SKP).

The proposed hierarchical gait descriptor realizes two different kinematic codings: at local trajectory level and at regional clustering level. From a local level, the proposed strategy is focus on the computation of atomic kinematic structures that allows to describe relevant gait features. Hence, a inter-trajectory relationship was achieved by coding the associated dense flow as a circular binary pattern. The spatial motion pattern (SMP) captures velocity profiles around trajectories by comparing local appearance changes in consecutive frames [22]. This idea was here extended by computing spatial kinematic patterns (SKP) that correspond to dynamic relationships from the local velocity field around trajectories. For doing so, along trajectories is drawn a circular grid with radius r, centered at trajectory the positions: (P_t, P_{t+1}) in consecutive frames. Around each circular grid is defined a set of patches that recover primitives information w.r.t intensity and velocity field in surrounding neighborhood. Then, the kinematic similarity pattern is defined as the sum of squared dif-

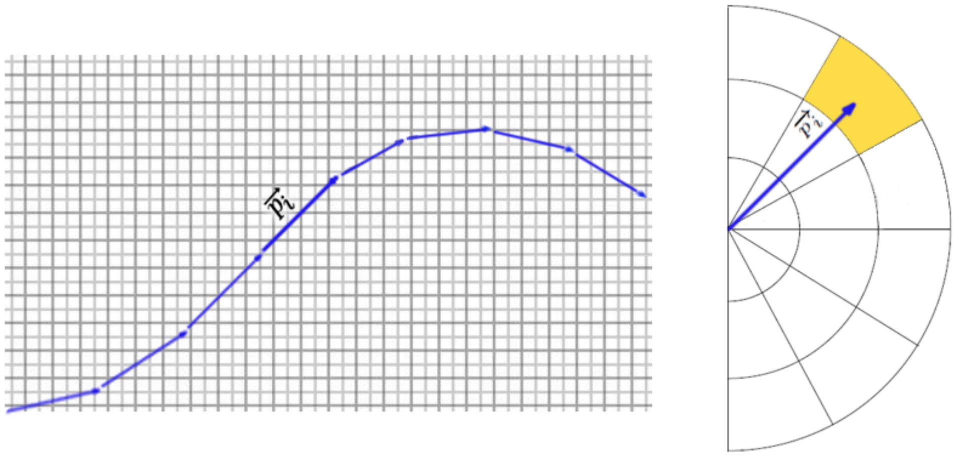

Figure 3: Semi-circular dartboard representation. The $2D$ displacement between consecutive frames across each trajectory (left) is coded in a semi-circular dartboard (right) considering the horizontal translation invariance of gait.

ferences (SSD) of consecutive patches at the same circular location. Let $\left\{\Delta(p,t)_i^k\right\}_{i=0}^{n-1}$ be the set of n patches around trajectory p at frame t. The corresponding SKP codeword b^k is calculated for each i-th patch as follows:

$$b_i^k = \begin{cases} 1, & \text{if } SSD\left(\Delta\left(p,t\right)_i^k, \Delta\left(p,t+1\right)_i^k\right) \geq \tau \\ 0, & \text{otherwise} \end{cases} \tag{2.1}$$

where k correspond to the three different maps, namely: intensity, magnitude and orientation of associated dense flow. The τ is a threshold to recover a binary vector (see in Figure 2). This encoded SKP descriptor at each position is labeled with zero if its motion is close similar to the center of particle, and 1 otherwise. The resulting descriptor captures kinematic relations of moving segments along their trajectories. Additionally, this local descriptor captures geometric shape around trajectories, and result robust against complex background scenarios.

2.2.2 Semi-circular Dartboard.

Pathological parkinsonian gaits symptoms usually are expressed in terms of velocity variations with respect to the normal gait patterns. Taking such fact into account, a semi-circular polar coding was here used to represent velocity information of trajectories. Let $\overrightarrow{p}$ be the 2d displacement of the particle between frames t and $t+1$. We construct a half-dartboard quantization of vector $\overrightarrow{p}$. This semi-circular dartboard is invariant to horizontal gait translation. In our implementation, we used intervals of $\frac{\pi}{6}$ for the angles and 2 pixels for the norm where the last interval goes from 6 to +inf. since gait is characterized by being indifferent to the direction of displacement, angles from -90° to 90° are finally considered, resulting in a 24 bins dartboard (as depicted in figure 3). Then, angles are displaced from 0 to 180° to get a representation with only positive values. The resultant semi-circular dartboard descriptor complement local information of SKP and allows to weight speed gait patterns to discriminate in a better way parkinsonian patterns.

2.2.3 Clustering.

Much of the proposed markerless strategies are only focus on global shape characterization during gait, losing sensibility on description of localized movements. For instance, upper and lower limbs describe parkinsonian patterns that should be treated independently during kinematic analysis. Taking into account such considerations, a second step in this work was a spatio-temporal body segmentation, to approximate anatomical segments, achieved by grouping the dense trajectories according to the localization and motion information. The whole trajectories were aligned with respect to the time axis and then an affinity matrix was computed among the corresponding points of each trajectory. The distance of similarity herein implemented to compare trajectories is described in [25], and expressed as:

$$d(a,b) = \underset{n \in [1,L]}{max} (d_{spatial}[n]) \cdot \frac{1}{L} \sum_{n=1}^{L} d_{velocity}[n] \tag{2.2}$$

, where L is the length of trajectories, $d_{spatial}[n] = |xa[n] - xb[n]|$ is the vertical distance of the trajectory points and $d_{velocity}[n] = |\dot{x}a[n] - \dot{x}b[n]|$ is the distance of local trajectory velocities. Such distance penalize trajectories that are vertically far apart and associate trajectories with similar velocity patterns. An affinity matrix is then obtained as $w(a,b) = exp(-d(a,b))$ computed at each trajectory pair. The affine matrix has dimension of: $T \times T$, where T is the number of trajectories in the video. To ensure compactness, trajectories that are not spatially close are forced to zero: $max(d_{spatial}) \geq 120$. Then, an affinity matrix serves as input of a K-means to perform an automatic clustering. The spatio-temporal clustering herein achieved allows a localized kinematic analysis of each region, which could be relevant to analyze and localize significant signs associated with the disease. The figure 1 the third row shows the result of run five different clusters using the affine trajectory matrix.

2.2.4 Coding and Prediction of Regional Kinematic Patterns.

A second kinematic description is here achieved by describing the trajectories relationships that are related with a body segment during gait. This regional descriptor is coded as the occurrence of the SKP. For doing so, a bag-of-words scheme was adopted by building a general kinematic dictionary and specific representative histograms for each regional group. Then, independent codebooks were built with respect to the primitive coded in SKP, *i.e.*, the intensity, the speed and the orientation. Each codebook was built from a k-mean clustering, fixing k with respect to the clinical gait analysis. Each SKP word is mapped to the dictionary using a Euclidean distance and a voting process is implemented to closest centroid. This histograms allows to describe rigid parts during locomotion, and stand out kinematics that statistically describe the different phases of gait according to type of motion. These histograms represent the gait descriptor of the video sequence being dependent of SKP.

Taking into account such regional quantification a useful way to analyze the descriptive character of each region is from a classification setup. In such case, the resulting gait descriptor is mapped to a previously trained data learning strategy to perform an automatic classification. In this work was implemented a Support Vector Machine (SVM), a technique widely used in many problems of supervised learning because the proper trade-off between accuracy and computational cost [7]. For data classification, the classes represent the types of gait and the optimal hyperplanes separate them using a classical maximum-margin formula. A parameter sensitivity analysis (γ, C) was performed with a parameter search using a k-fold cross validation scheme and selecting the parameters with the highest number of true positives. Because, gait patterns are namely associated to non-linear behaviors, a Radial Base Function (RBF) kernel was herein implemented to learn hyperplanes of classification.

Chapter 3

GAIT DATA

Validation was carried out with recorded sagital views, registered at the foundation **FAMPAS** *(Fundación del Adulto Mayor y Parkinson Santander)*, under semi-controlled conditions. This study was approved by the Ethics Committees of the Universidad Industrial de Santander. Written informed consent was obtained by the parents considered in this study. The dataset consists of a set of videos captured from 14 participants, being 7 patients diagnosed with Parkinson disease and 7 control patients. The captured gait data has an equal gender distribution of seven women and seven men. The parkinsonian patients were classified by an expert in stages 2 and 3 of the disease. A total of 84 video sequences were recorded, in which each subject in the study was recorded 6 times while perform a natural markerless walking. The whole set of videos were recorded in indoor scenarios with different clothes. The background is relative static with some challenges regarding to illumination changes. The sequences were spatially and temporally downsampled to 25fps and 800x480 pixels. This dataset is public for academic purposes and it is available in [1].

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[1] https://uis-macv.github.io

Chapter 4

EALUATION AND RESULTS

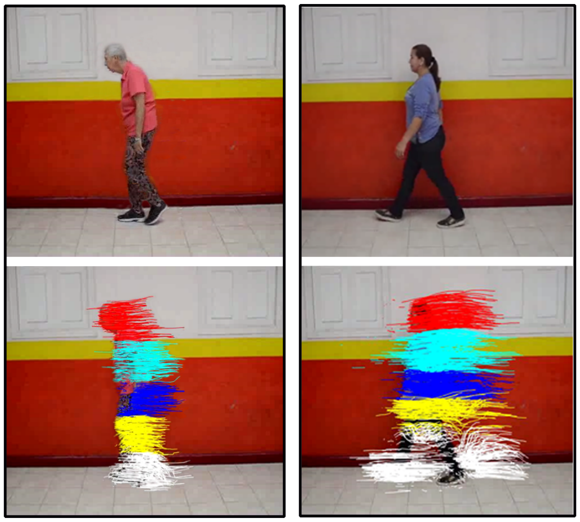

Figure 1: Comparison of parkinsonian gait trajectories (left) and a normal gait trajectories (right). Between the parkinsonian and control gaits is appreciable the difference in length and waviness of the trajectories. Also rigidity and dynamic description of head could be considered into a observational analysis.

The experimental evaluation of the proposed approach was performed over a set of markerless gait videos in two different populations: parkinsonian and control patients. A binary classification scheme was herein implemented to analyze the performance of regional gait descriptors. The set of motion trajectories were computed on a grid spaced by 5 pixels and tracked in 8 different spatial scales, to achieve a trade-off between accuracy and computational cost. The SKP was fixed in a circular configuration of 16 patches with a size of 3×3 and a radius of 9 pixels. The regional clustering was run with $K = 5$

clusters for K-means, which allows to consider main observable segments from a sagital point of view. Then, each regional histogram was defined with a dimension of 100 with a global normalization using L1-norm.

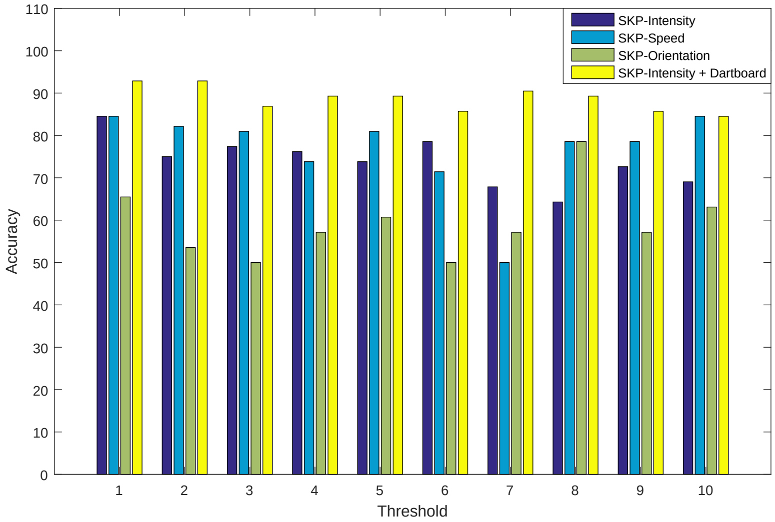

Figure 2: Variation of the accuracy with respect to the SKP threshold τ. Adding trajectory velocity from the semi-circular dartboard improves the results significantly.

In Figure 1 is illustrated a typical trajectory representation in parkinsonian and normal gaits. In this Figure, the trajectories clustering achieves a kinematic description of main body segments involved in locomotion. For instance, in lower limbs the reduced footstep size can be observed as dense trajectory with small displacement among feet. For normal gait is observed well separated foot trajectories with a larger displacement of the trajectories. Also swing arm rigidity can be captured by local dynamic of trajectories showing fewer undulations along motion

A first quantitative experiment was carried out by analyzing local variation of the computed SKP. For doing so, the threshold τ, that express the binary pattern sensibility, was progressively changed from the different primitives. For this experiment the number of words in the BoW representation was set to 200. In figure 2 is reported the obtained result for the different τ values, being remarkable the stable performance of binary patterns related with speed and appearance differences in almost all values. In $\tau = 10$ the speed binary patterns achieve an average accuracy of $84,52\%$, which could be associated with the characteristic frequency in parkinsonian disease. Moreover, Adding the semi-circular dartboard information to the SKP of intensity present a significantly improvement,

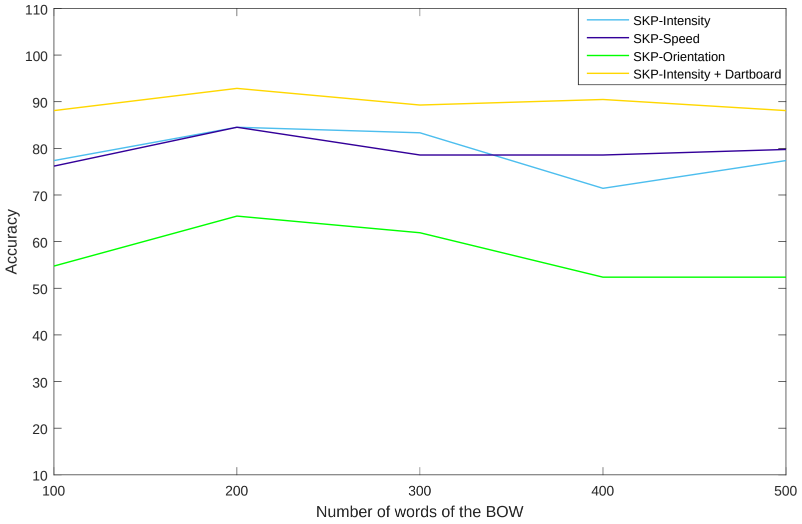

Figure 3: Variation of accuracy with respect to the number of words for the BOW representation. A best trade-off between accuracy and compactness is achieved with $\sim [200 - 300]$ words.

achieving an average accuracy of $92,87\%$. In the other hand, the orientation patterns in almost all cases has a lower performance which can be associated to the computation of background noisy patterns that affect the gait modeling.

In a second experiment the regional kinematic description was evaluated by changing the dimension of gait descriptor. As observed in figure 3, the proposed approach only requires 200 scalar values to represent a global gait descriptor, and achieving an average accuracy of $84,52\%$ in speed and appearance difference primitives and $92,87\%$ taking into account the trajectory velocity information. In general for the evaluated range of values, the proposed approach is stable, requiring less than $\sim\ 300$ scalar values for represent gait, fact that can be considered computationally efficient.

Finally, an independent region analysis was carried out to power of description of each region w.r.t the parkinsonian patterns. A global clustering of five regions was spatially achieved during locomotion (see in figure 1). Interestingly enough, the proposed approach achieve a proper recognition of parkinsonian patterns for individual computed regions, obtaining an average of $64,76\%$ for SKP and $91,67\%$ for SKP combined with the semi-circular dartboard. The best performance of SKP is captured in patterns related with legs (R4, R5) by the regional descriptor built from the primitive of speed. Meanwhile, considering the trajectory velocity information the regions corresponding to the arms (R2,

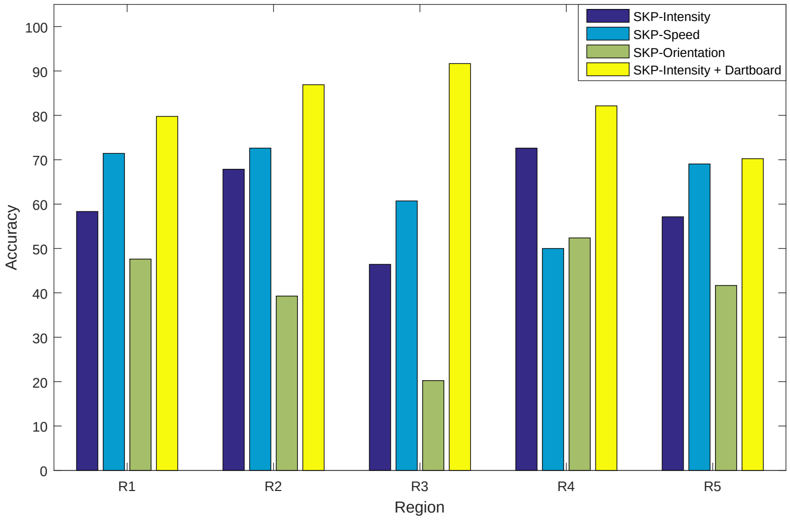

Figure 4: The results obtained by region for each of the maps individually.

R3) present outstanding results. Such results are fully associated with parkinsonian clinical reported patterns. The arms rigidity is also captured by the proposed SKP, obtaining an average accuracy of $60, 71\%$ for region R3. The region R1 also shows a proper performance, which is related with head motion patterns. For this local analysis, we use 100 words for the BOW.

Chapter 5

CONCLUSIONS

This work presented a novel markerless approach that allows a hierarchical kinematic analysis from a set of dense trajectories representation. In a low level analysis a spatial kinematic patterns (SKP) are built from circular binary patterns computed from consecutive frames and the associated motion field. Such SKP are captured along trajectories and allows to describe local structure of object dynamics. In a second regional analysis, the SKP computed for each trajectory are clustered in corresponding body segments. From such regions are computed occurrence histograms that define predominant kinematic patterns of each segment during locomotion. From experimental evaluation, the SKP computed from speed of motion field demonstrated be robust in parkinsonian pattern description. In contrast, orientation flow patterns are sensible to background changes with some limitations to represent gait motions. Furthermore, the descriptor outperform itself when is combined with velocity information of trajectories from the semi-circle dartboard. This results in a descriptor that is highly sensitive to velocity variations, which is the most representative kinematics characteristic of parkinsonian gait. Future works include a longitudinal evaluation to analysis the parkinsonian progression from a regional kinematic analysis.

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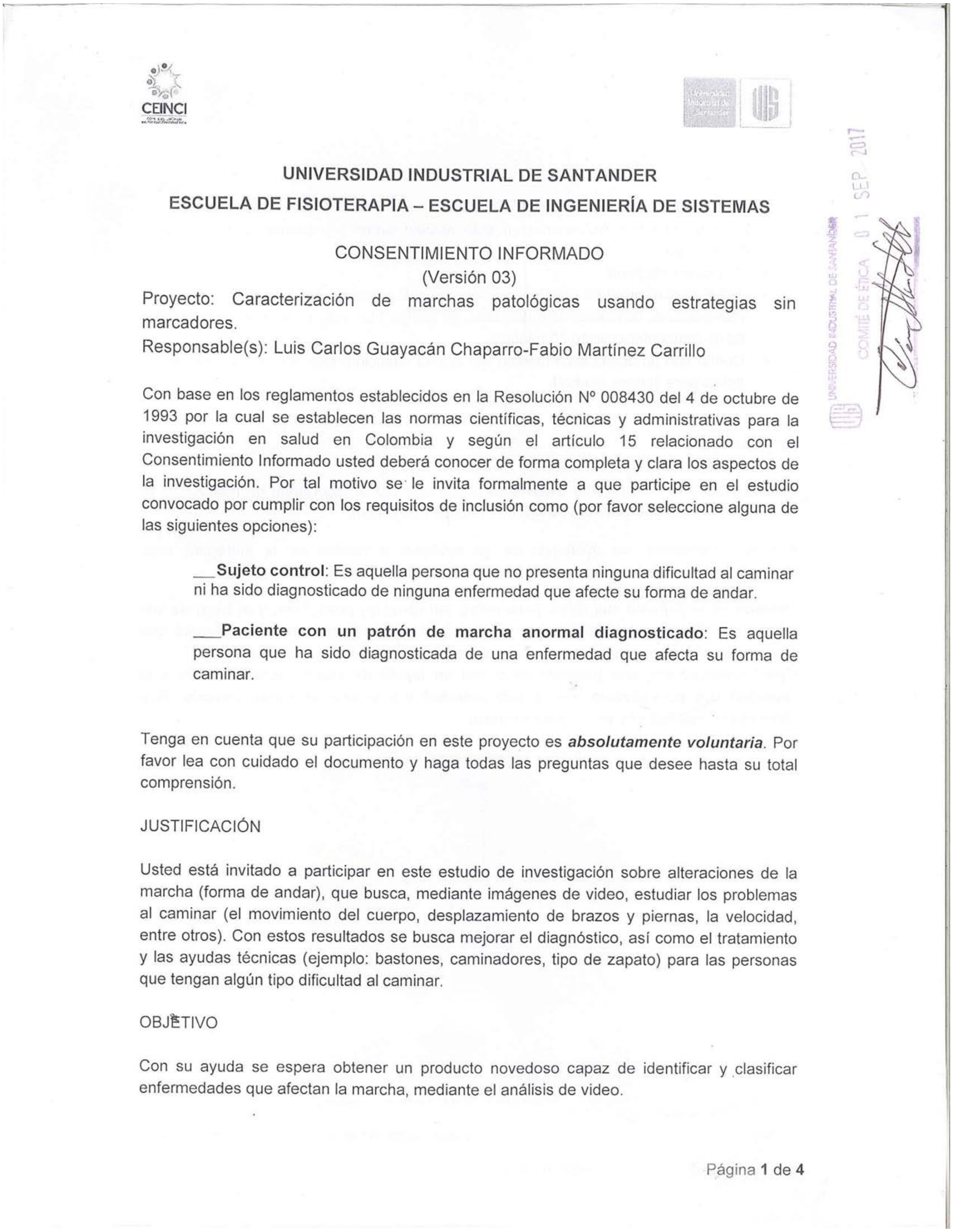
APPENDICES

A PRODUCTS

- A public markerless gait dataset. This dataset is public for academic purposes and it is available at https://uis-macv.github.io/datasets/datasets.html
- *Identificación automática de segmentos corporales utilizando un análisis cinemático de la marcha sin marcadores.* Fabio Martínez, Luis C. Guayacán. Poster presented to: *I Encuentro Internacional en Ciencias de la Salud: El Saber y la Tecnología al Servicio de la Vida. UIS Colombia 2017*.
- *Marinez, F., Guayacan, L.Parkinsonian gait characterization from regional kinematic trajectories.* Manuscript submitted for publication to "14th International Symposium on Medical Information Processing and Analysis: SIPAIM-2018".

B INFORMED CONSENT

Informed consent with the assent of the ethics committee: Comité de ética en investigación científica CEINCI of the Universidad Industrial de Santander in the 20th session on September 1, 2017.



CEINCI

UNIVERSIDAD INDUSTRIAL DE SANTANDER

ESCUELA DE FISIOTERAPIA – ESCUELA DE INGENIERÍA DE SISTEMAS

CONSENTIMIENTO INFORMADO

(Versión 03)

Proyecto: Caracterización de marchas patológicas usando estrategias sin marcadores.

Responsable(s): Luis Carlos Guayacán Chaparro-Fabio Martínez Carrillo

Con base en los reglamentos establecidos en la Resolución Nº 008430 del 4 de octubre de 1993 por la cual se establecen las normas científicas, técnicas y administrativas para la investigación en salud en Colombia y según el artículo 15 relacionado con el Consentimiento Informado usted deberá conocer de forma completa y clara los aspectos de la investigación. Por tal motivo se le invita formalmente a que participe en el estudio convocado por cumplir con los requisitos de inclusión como (por favor seleccione alguna de las siguientes opciones):

___**Sujeto control**: Es aquella persona que no presenta ninguna dificultad al caminar ni ha sido diagnosticado de ninguna enfermedad que afecte su forma de andar.

___**Paciente con un patrón de marcha anormal diagnosticado**: Es aquella persona que ha sido diagnosticada de una enfermedad que afecta su forma de caminar.

Tenga en cuenta que su participación en este proyecto es ***absolutamente voluntaria***. Por favor lea con cuidado el documento y haga todas las preguntas que desee hasta su total comprensión.

JUSTIFICACIÓN

Usted está invitado a participar en este estudio de investigación sobre alteraciones de la marcha (forma de andar), que busca, mediante imágenes de video, estudiar los problemas al caminar (el movimiento del cuerpo, desplazamiento de brazos y piernas, la velocidad, entre otros). Con estos resultados se busca mejorar el diagnóstico, así como el tratamiento y las ayudas técnicas (ejemplo: bastones, caminadores, tipo de zapato) para las personas que tengan algún tipo dificultad al caminar.

OBJETIVO

Con su ayuda se espera obtener un producto novedoso capaz de identificar y clasificar enfermedades que afectan la marcha, mediante el análisis de video.

REQUISITOS DE INCLUSIÓN Y EXCLUSIÓN

Ud podrá participar voluntariamente en este estudio siempre y cuando cumpla con los siguientes requisitos:

- Ser mayor de edad.
- Tener la capacidad de desplazarse sobre sus dos pies sin necesidad de la ayuda de otra persona, caminadoras o bastones. El tiempo estimado para la captura de video es de aproximadamente 30 minutos.
- Contar con un diagnóstico médico de alguna afección que altera su marcha (no aplica para sujetos control).

DESCRIPCIÓN

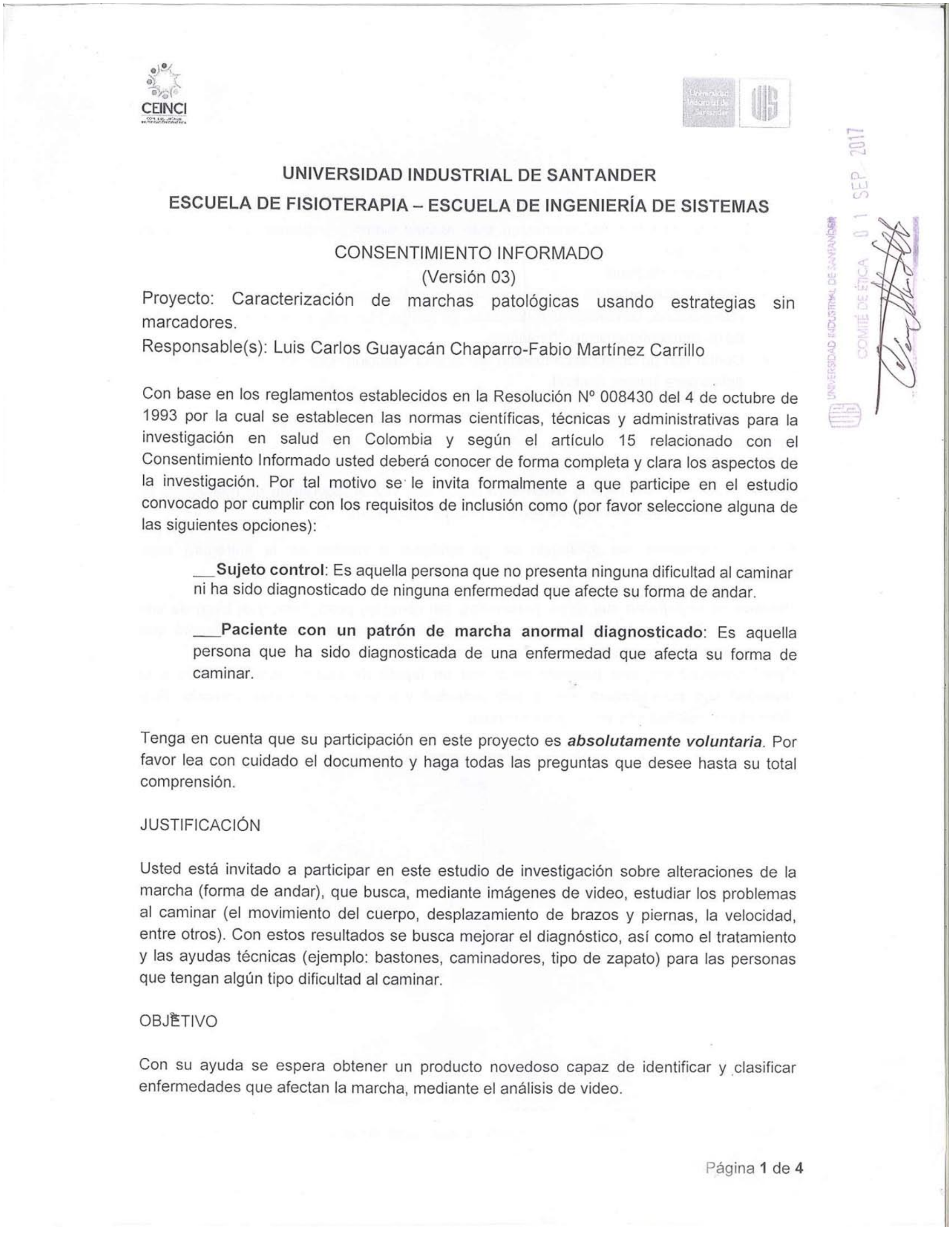
Para la realización del estudio usted será citado una vez al laboratorio de marcha de la Escuela de Fisioterapia (carrera 32 # 29-31 Facultad de Salud).

A cada participante, en presencia de un cuidador o familiar se le entregará este consentimiento para su lectura y si decide participar, podrá firmarlo.

Después se registrarán sus datos personales, así como su peso, talla, y el largo de sus piernas. La filmación del video tomará un tiempo aproximado de una hora, y tendrá que utilizar pantalón, pantaloneta o sudadera (no podrá utilizar faldas ni vestidos).
Usted caminará por una pasarela (piso con un tapete de caucho antideslizante) a la velocidad que normalmente realiza esta actividad y a la que se sienta cómodo. Esta caminata la realizará tres veces y será filmado.

Imagen 1. Persona caminando sobre una pasarela.

Al participar en este estudio, usted no tendrá que pagar ningún dinero, ni deberá colocar



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Con su ayuda se espera obtener un producto novedoso capaz de identificar y clasificar enfermedades que afectan la marcha, mediante el análisis de video.

Sin embargo, con el objetivo de realizar un manejo adecuado de los datos, un miembro del Comité de Ética de la Universidad Industrial de Santander podrá consultar sus datos y su registro.

Por lo anterior, atentamente se le invita a participar en el estudio y si está de acuerdo, se le solicita su nombre y la firma en las casillas abajo descritas.

Yo____, identificado con ______ N°_____________________de_____________________Consiento participar de manera voluntaria en el presente estudio. He leído y entendido la información registrada en este documento y al tener dudas, estas fueron aclaradas.

Entiendo que soy libre de retirarme del estudio, sin necesidad de dar alguna explicación adicional. Por otro lado, me han garantizado la confidencialidad, justicia, equidad y autonomía en la participación y manejo de toda la información que aquí se recolecte.

La información obtenida podrá ser divulgada con fines científicos, mediante presentaciones en congresos o publicaciones en revistas científicas, protegiendo la identidad de los participantes y garantizando la confidencialidad en el manejo de toda la información recolectada.

____

Firma del Participante

________________________________	________________________________
Nombre del Investigador	Firma del Investigador c.c.

Fecha: ______________________________

Contacto Comité de Ética: Para preguntas o aclaraciones acerca de los aspectos éticos de ésta investigación pueden comunicarse con el Comité de Ética para la Investigación Científica de la UIS (CEINCI-UIS), o con cualquiera de los miembros del Comité, al teléfono 6344000 Extensión 3808 ó al correo comitedetica@uis.edu.co.