Lagrangian center of mass (CoM_t) magnification to stand out main parkinsonian gait events

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***Abstract*—Gait analysis is crucial in Parkinson's disease (PD) diagnosis to clinically observe and quantify abnormal motor patterns. A primary gait biomarker is the center of mass trajectory (CoM_t) that express the global coordination of forces, neuromotor commands and musculoskeletical poses. Also, from such trajectories is possible to analyze main locomotion moments (LM), such as forefoot, midfoot and heel strike, commonly altered in PD. However, the CoM_t requires additional devices, e.g. force platforms, limited to only a few steps or markers associated in video analysis but altering the natural motion gesture and losing description of LM. This work introduces a markerless approach to compute the CoM_t followed by a Lagrangian global magnification. Additionally, a magnified video reconstruction allows to better observe gait patterns, useful for medical observation analysis. The Evaluation was performed on a control (7 patients) and PD (7 patients) video set, achieving a proper LM description w.r.t raw CoM_t captured in videos.**

***Index Terms*—Center of Mass Magnification, Parkinsonian Movements, Lagrangian Motion Magnification**

I. Introduction

Parkinson's disease (PD) is the second most common neuro degenerative disorder in the world, with around 6.3 million reported cases [1]. According to the Colombian Association of Neurology, more than 220,000 cases are currently estimated in Colombia. This disease is caused by the lack of the neurotransmitter known as dopamine, mainly producing motor symptoms, such as involuntary and sudden movement of limbs, stiffness, posture problems and gait disturbances [2]. During the clinical routine, the first analysis is developed in an observational way, where clinical experts evaluate the patient's motor patterns and try to identify specific symptoms of the disease. The evaluation can be supported mainly in the analysis of gait, clinical history, physiological and neurological examinations, among others. However, a timely diagnosis is often affected by the high variability and subtlety on the observed symptoms, leading to subjective and varying conclusions depending on the experience of the clinical expert [3].

Gait patterns can be highly descriptive and play a fundamental role as a PD biomarker since the locomotion process requires the integrity and interaction of different neural subsystems [4], [5]. PD patients may show significant changes in the heel to toe motion of the foot during gait, as well as shortened stride length, reduced velocity and abnormal postures to maintain the control [6]. The traditional observational analysis of these movements requires the support of some metrics to define quantitative differences between normal and abnormal patterns. For doing so, a variety of technical tools have been introduced to aim for a more objective gait analysis, among which the center of mass trajectories (CoM_t) stand out to providing a rich kinematic description of locomotion moments. The CoM is the point where all acting gravity forces are applied over the body, representing the centroid of the lower limb, pelvis, trunk, head and arm segment masses. Therefore, the CoM_t in clinical analysis in human gait is useful to evaluate walking efficiency and balance, reflecting the biomechanical performance of the whole body [7]. Current methodologies to capture and analyze such descriptor require sophisticated protocols and fully controlled environments, e.g., based on markers strategically positioned in certain body segments to provide instantaneous position through infrared cameras [8]–[10], or using force platforms in which the motion of the horizontal CoM projection is estimated from the measured vertical force component according to Newton's second law [11], [12].

Regarding PD, Bengevoord, *et al.* [13], studied the freezing of gait (FOG) disturbance, reporting a forward CoM_t shift and a decreasing step. This analysis was achieved using a 3D motion capturing system, with eight cameras. By a similar protocol, from parkinsonian CoM_t trajectories were reported step and stride length reduction, and the need to execute more steps to cover similar distances w.r.t controls [14]. Additional motor variables have been studied to complement CoM_t analysis. For instance, in [15] was found a decreasing vertical ankle displacement, accompanied by poor vertical foot lift off the floor. Such deviations contributed to a greater variety of the stride coefficient, indicating a less rhythmic gait. The capture of whole such variables depends on almost all cases of sophisticated laboratories and camera configurations, restricting the natural development of walking. Additionally, there exist a lack of flexible and simple methods that can be used in difficult environments, either to support and quantify the diagnosis or as a first step to rehabilitation.

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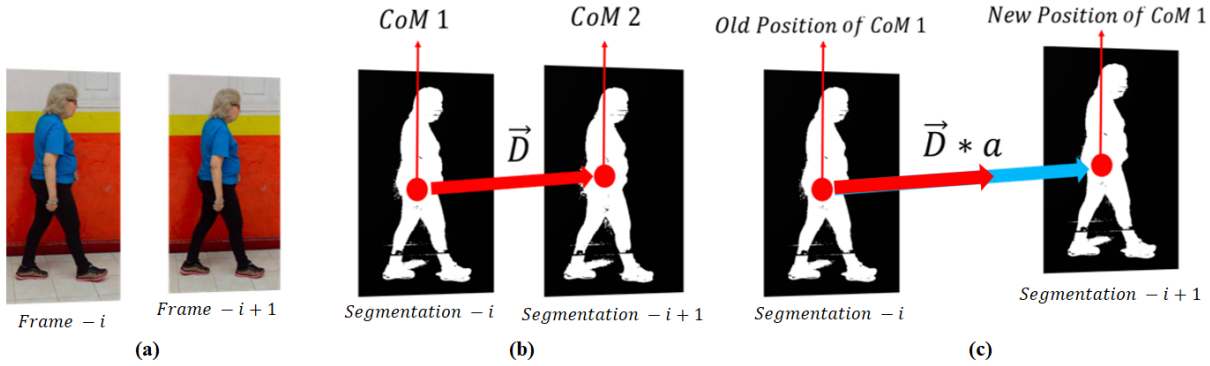

Fig. 1. Proposed pipeline to magnify CoM motion in a gait sequence. (a) Consecutive frames in a gait sequence, (b) The person silhouette is computed from a Gaussian background subtraction and the position of CoM is estimated from the obtained silhouette mask. The CoM$_t$ vector between consecutive frames is called $\overrightarrow{D}$. (c) $\overrightarrow{D}$ is amplified by an α factor and the CoM is relocated according to the new $\overrightarrow{D} * \alpha$ position.

On the other hand, in the early stages of the disease, abnormal movements can occur at very low magnitudes, making them imperceptible to the expert eye and thus limiting observational analysis.

In this work is introduced a markerless strategy to characterize the center of mass trajectory during gait, standing out main strike events. Firstly, an automatic body segmentation is achieved by using a background mixture of Gaussian subtraction. The recovered body serves as input to compute the center of mass at each time of the gait cycle. The resulting CoM$_t$ vector is then augmented by a α factor that allows exaggerating and better describe the main phases of locomotion. From such augmented gait version, pixels corresponding to silhouette are back-propagated to augmented locations, to reconstruct a new magnified video sequence. This sequence allows to experts better observe changes during gait to describe pathological behaviors. Also, a quantitative CoM$_t$ characterization was herein obtained, allowing to observe main strike moments. Next subsections describe the proposed strategy.

II. Proposed Approach

The pipeline of the proposed approach is illustrated in Figure 1. Firstly a background body subtraction is obtained to quantify the CoM at each time of the video. Then, a Lagrangian strategy allows to globally augment the CoM$_t$ to stand out main gait moments. Such augmentation also allows recovering a new video sequence that exaggerates gait patterns to a better expert observation. In next subsections is described the proposed approach in detail.

A. Markerless body subtraction

Classical gait analysis is based on a set of markers that are followed to estimate kinematic patterns. Such markers are however invasive and alter the natural gesture of gait. In this work, a full automatic body segmentation was achieved by implementing a background representation from a Mixture of Gaussian model (MoG) [16]. The gait videos in this work were recorded with a relatively static camera. Hence, the background could be modeled as a normal distribution with the mean as a background pixel, bounded into a standard deviation limit. In this approach, the relative stable pixels are modelled as a set of k Gaussian, as: $B = \sum_{k \in K} w_k G_k(\mu, \sigma)$, where w_k represents a defined weight or importance for each Gaussian, while modes count the most common dynamics of pixels. Each of the Gaussian is recursively updated along time (μ_t^k, σ_t^k), allowing a better adaptation of changes into the scene. Once the background model is defined B a likelihood estimation is achieved by a simple subtraction with respect to each frame, defined as: $\Delta_t(x) = B_t(x) - I_t(x)$. From such rule, pixels with high difference regarding the background are defined as the body pixels.

In this work, a total set of $k = 5$ Gaussians result in a proper trade-off between accuracy and computational time. As shown in Figure 1, this approach was sufficient to segment the body along the gait cycle, allowing a markerless framework for further analysis.

B. Computing augmented CoM

Once the body region is segmented at each frame t, CoM is computed as the center position $(\bar{x}_t, \bar{y}_t)$ of the corresponding silhouette. This CoM is however smooth because of video resolution, losing in such cases the important foot features that allow to characterize a particular gait. Then, in this work is proposed a dynamic exaggeration of the gait by augmenting the displacement CoM, defined among consecutive frames $(t, t+1)$, as:

$$\overrightarrow{D} = <(x_t, y_t), (x_{t+1}, y_{t+1})>, \quad (1)$$

that expressed in Euler notation, could be defined as $||D||\dot{e}^{\theta}$ where $||D||$ and θ represent the magnitude and angle of displacement vector. In this representation, magnitude displacement is magnified by an α value, as $\alpha||D||\dot{e}^{\theta}$ that allows to map whole body pixels with this reference and exaggerate spatially the locomotion process. In spatial coordinates, the augmented CoM could be represented as: $\overrightarrow{D_M} = <\alpha*(x_{n+1} - x_n) + x_n, \alpha * (y_{n+1} - y_n) + y_n>$ as illustrated in Figure 1.

Fig. 2. Visual representation of the backpropagated reconstruction for gait. In left is illustrated the conventional video with smooth changes during time. In right, the magnified version allows to exaggerate gait patterns allowing a better observational analysis. A magnification of $\alpha = 4$ was used in this example.

C. Backpropagation of augmented Gait regions

A second main contribution of this work was a magnified video reconstruction that allows observing exaggerate gait patterns. In such a way, expert clinicians count with a novel tool to interpret easily gait information and providing visual support in medical diagnoses. To obtain a magnified video reconstruction, the body silhouette obtained at each time is proportionally displaced, regarding the magnified center of mass. Formally, the body silhouette $\mathbf{\Gamma(x,y)_t}$ is spatially moved w.r.t the α factor, *i.e.,* $\alpha\mathbf{\Gamma(x,y)_t}$. Each of the pixels that belongs to silhouette $\mathbf{\Gamma(x,y)_t}$ as a corresponding value of intensity in video, so $\mathbf{\Gamma(x,y)_t} \rightarrow I(x,y)$ if $\{x,y\}$ in Γ. Then, the color value of the respective pixels in Γ is also updated in new locations. The rest of the pixels remain with the respective configuration of the background.

A typical example of reconstructed video sequences is illustrated in Figure 2. As observed, the augmented video sequence exaggerates the periodic pattern, showing that the patient performs small jitters during displacement. During this observational analysis, could be analyzed that for PD sequences this kind of jitters and the step length is reduced along the video sequence.

D. Gait Data

The evaluation of the proposed approach was developed using a set of gait videos recorded from saggital views, registered at the foundation **FAMPAS** *(Fundación del Adulto Mayor y Parkinson Santander)*. The set of videos were captured under semi-controlled conditions and with a relative static camera. This study was approved by the Ethics Committees of the *Universidad Industrial de Santander* and written informed consent was filled out, respectively. The set of videos recorded a total of 14 participants, being 7 patients diagnosed with Parkinson disease and 7 control patients. The set of data has equal gender distribution and the patients diagnosed with Parkison were classified in stages 2 and 3. Each of the recorded sequences has a spatial resolution of 800×480 at 25 fps. This dataset is public for academic purposes and it is available in [1]

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

III. Evaluation and Results

The magnification of CoM_t is the result of multiple α by the respective vector $\overrightarrow{D}$, conditioned to spatial dimensions of the video. The best values for were found with configuration $\alpha = \{2, 4\}$. The evaluation was carried out to quantify the gain of augmented CoM_t trajectories, in terms of better gait moment description and proper differentiation between PD and control classes. In Figure 3 is illustrated typical CoM_t trajectories, wherein blue is plotted the standard computation of the CoM signal, and in red its magnified version. Figure 3-(a) was magnified with a factor of 2, while Figure 3-(b) a factor of 4 was used, both for a PD patient. In the same configuration, Figure 3-(c) and 3-(d) represent magnified CoM trajectories with a factor of 2 and 4 for a control patient, respectively. As expected, the magnified CoM_t version stand out main gait moments, allowing to establish well defined boundaries between both motion classes. While for control trajectories the first peak that represents heel strike is well defined, on parkinsonian sequences is observed a smooth decay during the foot support. Also, for control patients could be observed well-defined steps that properly identify the gait cycle. Additionally, push-off and propulsion are relatively smooth w.r.t the defined in control patients.

The cross correlation was herein used to validate the information represented by the original and augmented CoM_t trajectories. This metric measures how much one CoM signal resembles another for certain amounts of phase shift. This is defined in: $(\text{CoM}_k \star \text{CoM}_m)[n] = \sum_{i=a}^{b} \text{CoM}_k[i]\,\text{CoM}_m[i+n]$, where $\text{CoM}_{k,m}$ are the compared signals, n represents the phase offset, and a, b are the initial and final reference points. In Figure 4 is summarized the cross correlation of CoM_t trajectories, considering different raw and magnified versions, as well as an inter-classes comparison, as: PD vs PD, control vs control and control vs PD. Two different experiments were carried out from complete video sequences, and using crop gait cycles to locally compare shape of specific signals.

Regarding comparison of complete video sequences, Figure 4-(a) and Figure 4-(b) show the results obtained for raw and magnified comparison, respectively. As expected, the magnified version (subplot-b) achieves a larger difference between PD and control patients. In this experiment, for complete video sequences comparison, the result could be associated

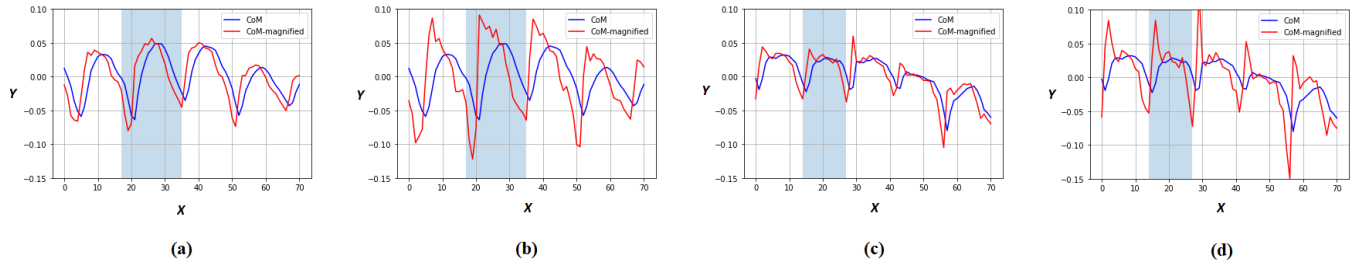

Fig. 3. Graphical comparison of obtained CoM trajectories. **(a)** Original and magnified positions of CoM for a sample PD patient using $\alpha = 2$ and $\alpha = 4$ respectively. In these graphics, it is important to highlight the smooth movements described by the CoM_t, as a sign of the presence of Parkinson's disease.**(b)** Original and magnified positions of CoM for a sample control patient using $\alpha = 2$ and $\alpha = 4$ respectively.

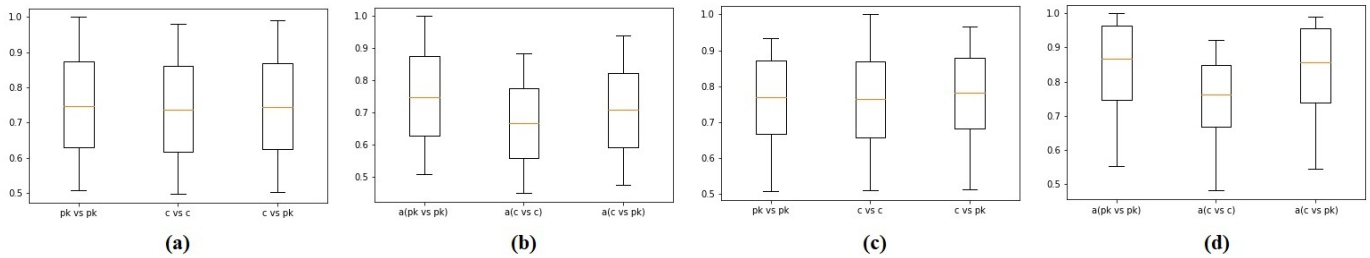

Fig. 4. Boxplot of the averaged cross correlation signals. Inter-class comparison is considered, where *pk* stands for PD CoM trajectories and *c* stands for control CoM trajectories. **(a)** Global cross correlation by taking the whole CoM_t sequence of both Classes. **(b)** Global cross correlation with magnified CoM_t sequences. **(c)** Local cross correlation by taking representative CoM segments for both Classes in short displacements. **(d)** Local cross correlation with magnified CoM_t sequences.

with the larger occurrence of parkinsonian steps w.r.t control trajectories. In the second evaluation, the CoM_t trajectories were split on complete gait cycles to perform a localized evaluation of trajectories. In this evaluation, boxplots of Figure 4-(c) and Figure 4-(d) correspond to the local cross-correlation of the original and magnified CoM_t trajectories, respectively. During this evaluation also could be observed that relevant information is highlighted in both classes, allowing a better definition of normal and abnormal boundary patterns.

Additionally, the mean quadratic error between augmented and original CoM signals was calculated for control and PD patients, to establish differences between classes. Obtained results are summarized in table. It might be noted the close local similarity of augmented CoM_t trajectories among similar classes.

TABLE I
MEAN SQUARE ERROR COMPARISON OF CONTROL AND PARKINSONIAN GAIT PATTERNS.

Signal	**MSE**
Global gait pattern, original motion	0.0106
Global gait pattern, magnified motion	0.0016
Local gait region, original motion	0.0176
Local gait region, magnified motion	0.0017

Lastly, the CoM trajectories were coded as a motion descriptor to classify control patients and PD patients using the K Nearest Neighbor algorithm (k-NN) [17]. KNN is an unsupervised learning algorithm able to perform simple classification tasks, being non-parametric, that is, do not reply to any particular assumptions over your input data. Given a certain data to perform classification, the algorithm searches for the most nearly k neighbors (which in this case is measured in Euclidean distance) and assign a class according to of the number of labels in the k neighborhood. The k-NN algorithm is ideal for working with small volumes of data. In this work, by using the data previously described with $\alpha = 4$, an accuracy of 69% was obtained in the classification of control and PD patients.

IV. CONCLUSIONS

This work presented a simple but effective approach to augment CoM_t trajectories, that allows to characterize parkinsonian patterns. The proposed approach coded the CoM from a markerless approach, allowing a natural locomotion displacement. Then a Lagrangian magnification highlights strike moments of gait, fundamental to identify abnormal patterns. An exhaustive evaluation shows the advantages of compute augmented CoM patterns to reveal fundamental information about physical condition of patients. Finally, the augmented body silhouette allowed to reconstruct an augmented video, useful during clinical observational analysis.

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