PATHOLOGY CLASSIFICATION OF GAIT HUMAN GESTURES

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Abstract: Gait patterns may be distorted in a large set of pathologies. In the clinical practice, the gait is studied using a set of measurements which allows identification of pathological disorders, thereby facilitating diagnosis, treatment and follow up. These measurements are obtained from a set of markers, carefully placed in some specific anatomical locations. This conventional procedure is obviously invasive and alters the natural movement gestures, a great drawback for diagnosis and management of the early disease stages, when accuracy is a crucial issue. Instead, markerless approaches attempt to capture the very nature of the movement with practically no intervention on the movement patterns. These techniques remain still limited concernig their clinical applications since they do not segment with sufficient precision the human silhouette. This article introduces a novel markerless strategy for classiying normal and pathological gaits, using a temporal-spatial characterization of the subject from 2 differents views. The feature vector is constructed by associating the spatial information obtained with SURF and the temporal information from a Σ-Δ operator. The strategy was evaluated in three groups of patients: normal, musculoskeletal disorders and parkinsons disease, obtaining a precision and a recall of about 60%

1 INTRODUCTION

Distortion of gait patterns are the first clinical manifestation of many diseases, among others diabetes, brain palsy or accident sequelae. The analysis of human gait attempts to objectively assess pathologies by following up the hidden gait dynamic variables. The set of techniques dedicated to perform this analysis is what is currently known as the gait laboratory, a tool devised to quantify a disease and to compare the gait with normal patterns (Perry and Burnfield, 2010), (Haiyan Luo and et al., 2010). Most of this gait analysis is carried out with a set of markers, carefully placed upon some specific anatomical locations. This conventional procedure is invasive and alters the natural movement gestures, necessitating strong variations to achieve diagnosis, i.e., this approach is hardly useful in early stages.

On the other hand, gait dynamic patterns are by nature highly variable and can be easily contaminated with noise. In early stages, most of these diseases differ by very little from what is considered a normal pattern so that classification is a very challenging problem, even for the expert clinicians. This picture may be worsen if one considers that the basic examination tool, the markers, can move very easily or can even be unobservable, contaminating the resulting measurement. These factors together lead to subjective clinical analyses with the consequent limitation in the reproduction of the clinic management of the patient (Kamruzzaman and Begg, 2006), (Wolf and et al, 2006).

Ultimately, this problem has undergone a fundamental transformation since the objective is not anymore the movement reconstruction from the anatomical markers, but the accurate tracking of the movement pattern i.e. the markerless strategy. Research areas as computer vision, automatic surveillance, animation and image processing have already developed some markerless strategies for diverse applications, namely, biometric identification, abnormal motion detection, scene reconstruction and activity classification (Turaga et al., 2008), (Klempous, 2009). However, there are several problems related to extracting the object of interest from some escenaries, mainly due to the blurred boundaries between the background and foreground (Cristani et al., 2010), (McHugh et al., 2009), an issue that can result in wrong characterizations.

This article presents an efficient markerless methodology to identify and classify different kinds of normal and pathological movements. A non linear Sigma-Delta (Σ-Δ) operator is used to obtain a temporal movement description as a set of pixels.

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Most of them correspond to a particular patient shape while some small scattered groups belong to the background. Afterwards, we compute a bounding box around of largest group and therein we calculate some local features per frame, using the "Speeded Up Robust Features"(SURF). A weighting function allows associating some of these spatial features with relevant temporal information. This weighted feature vector is used to classify patterns as normal or pathological, applying a classical Support Vector Machine strategy. Evaluation was performed on a database with 96 videos from 32 patients, with three types of movements: normal, musculoskeletal disorders and Parkinson's disease. Sensitivity and specificity are used to assess the utility of this method. This paper is organized as follows: section 2 briefly outlines the nature of the dataset, section 3 introduces the proposed markerless strategy, section 4 sumarizes the results & the effectiveness of the proposed method, finally section 5 concludes with a discussion and possible future works.

2 GAIT DATA

Experimentation was carried out with video sequences recorded from 3 views frontal, lateral and 45 degree view, registered at the gait laboratory of the National University of Colombia, under semi-controlled illumination conditions. This dataset consists of a set of videos captured from 20 patients, each one was recorded 4 times while walking, for a total of 240 video sequences. The Dataset was divided as follows:

- 8 patients diagnosed with musculoskeletal disorders for a total of 13500 frames.
- 7 patients diagnosed with parkinsons disease (No depressive disorder present) for a total of 15500 frames.
- 5 patients with normal gait for a total of 14000 frames

3 THE PROPOSED METHOD

Our proposed method begins calculating the temporal information using a $\Sigma-\Delta$ operator. A bounding box is superimposed upon the region with the largest rate of change and the local features are calculated, within this box, using SURF. A weighting function chooses the more relevant SURF features, those with a similar spatial location to the pixels detected by the $\Sigma-\Delta$ operator, i.e., the features that contain temporal and spatial information. The obtained feature vector is used to classify patterns as normal or pathological, applying a classical SVM, as illustrated in figure 1.

3.1 $\Sigma-\Delta$ Temporal Estimator

Temporal description of the patient gait patterns is central at describing structural changes. Many strategies have been proposed already, they are currently known as background estimation methods (Elgammal et al., 2000), (Manzanera and Richefeu, 2007), (Howe and Deschamps, 2004). These methods use a sequence of images I_t and build up a model of the static scene M_t. The model output is an image D_t, where the background is represented by $D_t(x) = 0$ and the foreground is $D_t(x) = 1$.

Algorithm 1: $\Sigma-\Delta$ Algorithm.

```
Initialization: M_0(x) = I_0(x)
for each Frame t do
    M_t(x) = M_{t-1}(x) + sgn(I_t x - M_{t-1}(x))
    Δ_t(x) = |M_t(x) - I_t x|
end for
Initialize: V_0(x) = Δ_t(x)
for each Frame t do
    for each pixel x such that Δ_t(x) ≠ 0 do
        V_t(x) = V_{t-1}(x) + sgn(N × Δ_t(x) - V_{t-1}(x))
        if Δ_t(x) < V_t(x) then
            D_t(x) = 0
        else
            D_t(x) = 1
        end if
    end for
end for
```

In our dataset the silhouette extraction is a difficult task because of the similarity between the foreground and the background. Hence we use a non linear $\Sigma-\Delta$ operator to obtain a motion descriptor which detects the most probable localization of the foreground. This estimator oversamples a signal at higher rates than the especified by the Nyquist teorem, increasing correlation between the adjacent frames at each pixel (Manzanera and Richefeu, 2007). The $\Sigma-\Delta$ operator behaves as a background tracker $M_t(x)$, dynamically updated by comparing each image $I_t(x)$ with the current background $M_t(x)$, using a simple updating rule: If $I_t(x)$ is greater (lower) than $M_t(x)$, then a positive increase (decrease) $+\Delta$ is performed. The implemented $\Sigma-\Delta$ is shown in the Algorithm 1.

Upon the region with the largest movement pattern, we compute a center of mass, on top of which we place a bounding box that contains the object of interest. This process is speeded up using an integral image representation of the original images, reduc-

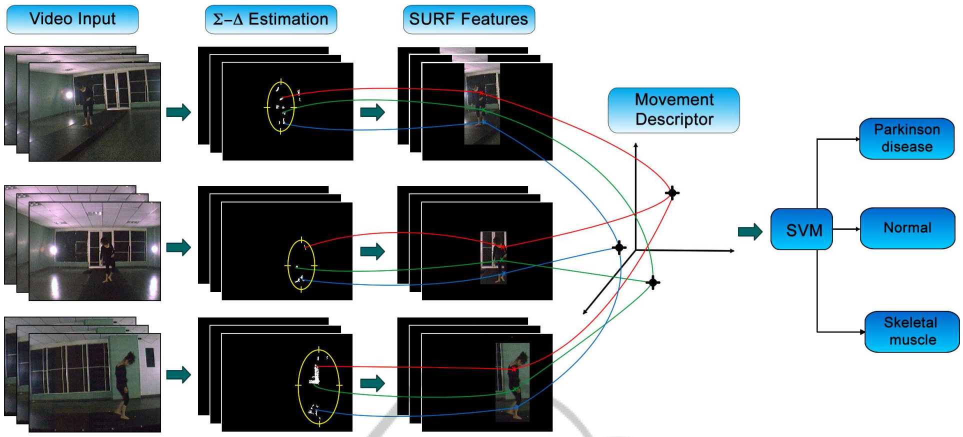

Figure 1: The markerless strategy consists in determining a feature vector to describe normal and pathological movement, using a temporal-spatial gait characterization. Motion is classified using a Support Vector Machine strategy.

ing the computational cost by 94% (Viola and Jones., 2004).

3.2 Speeded up Robust Features (SURF)

Once the bounding box is extracted, we calculate some local features of it using the Speeded Up Robust Features (SURF) descriptor (Herbert Bay and Gool, 2008). This descriptor highlights the salient points within the bounding box so that each salient point is described by magnitude, orientation and feature vectors. The SURF method provides invariant image description, allowing a robust representation against illumination, scale and rotation changes, a useful aspect in our problem due to the semi-controlled scenario, different views and patients.

The SURF description is obtained by initially computing the Hessian matrix $H(X,\sigma)$, as follows: -

$$H(X,\sigma) = \begin{bmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{bmatrix}$$

where X is a especific point, σ is the scale and $L_{xx}(X,\sigma)$ is the second Gaussian convolution. This step relies on an integral image to reduce the computational time. Afterwards, SURF constructs a circular region surrounding the points of interest, attempting to assign a unique orientation by estimating the Haar wavelet coefficients in both directions and thereby gaining invariance to image rotations. SURF descriptors are thus constructed by extracting square regions around the points of interest, which are divided in four sub-regions.

3.3 Feature Extraction

SURF features are used to obtain a summarization of the gait sequence, they operate exclusively on the bounding boxes. Once the set of SURF features is calculated, the values of the SURF descriptor vector are weighted, following the pixel intensity distribution obtained from the $\Sigma - \Delta$ operator. Higher values are assigned to vectors whose locations belong to regions with high movement. The proposed summarization is a collection of weighted vectors, arranged acording to their frame number, on the gait sequence.

As the SURF features produce a variable number of points of interest for different squences, the final descriptor of a gait sequence is obtained at quantizing the complete set of vectors into 5,10,20,40 and 50 clusters using the Expectation Maximization algorithm yielding 5 different descriptors for a single sequence.

4 EXPERIMENTAL RESULTS

Classifcation was performed using a Support Vector Machine (SVM), trained with a set of attribute vectors, extracted from labeled gait sequences. In this phase, two types of kernels were used, polynomial and Radial Basis Function (RBF) kernels. A sensitivity analysis of the parameters, gamma (RBF kernels) and the exponent (polynomial kernels), were estimated using the sequential minimal optimization algorithm (Flake and Lawrence, 2001), the parameter which yielded the larger number of true positives.

Table 1 shows the precision, recall, and sensitivity, obtained with either the RBF or the polinomial kernel.

Overall, the SVM strategy shows precision and re-

Table 1: Table shows the precision, recall and sensitivity for the different evaluated classes, i.e., the musculo-skeletal disorder (M), the normal pattern (N) and the parkinsonian gait (P), using both the RBF and polynomial kernels.

Class	Precision		Recall	
	RBF	Poly	RBF	Poly
M	0.67	0.75	0.33	0.75
N	0.6	0.7	0.95	0.66
P	0.72	0.61	0.41	0.64

call figures above 0.6, except for the musculo-skeletal patterns, for which the RBF is 0.33, a very large difference that can be attributed to the fact that the group of musculo-skeletal is composed of a larger number of patterns and therefore the variance is much larger. The RBF kernel shows a recall of 0.95 for the normal group, indicating that the RBF kernel works better with the data with smaller variance. Of course the fact that the normal group was the larger group (8 cases, compared with 7 and 6) can bias these results, together with the fact that the chosen parameters were set by the fact that they detected the larger number of true positives.

Table 2: Confusion Matrix using RBF and polynomial kernels for the three evaluated classes.

Class	M		N		P	
	RBF	Poly	RBF	Poly	RBF	Poly
M	4	9	5	1	3	2
N	1	2	20	14	0	5
P	1	1	8	5	8	11

Likewise the confusion matrix shows that correlation between the nomal class is the higher.

5 CONCLUSIONS

This paper has introduced a novel markerless method that allows to characterize normal and pathological human gait patterns. The whole markerless strategy consists in determining a feature vector for describing normal and pathological movement, using a temporal-spatial gait characterization from 3 differents views. The feature vector is constructed by associating the spatial information obtained from SURF and the temporal information from a $\Sigma - \Delta$ operator. Motion is classified using a classical Support Vector Machine strategy. Results demonstrate that this method can complement the conventional gait analysis since it assigns objective pattern measurements. The methodology presented in this work constitutes a first approximation to understanding the complex dynamic of the gait. From this kind of analyzes, we expect it would be possible to set up an assembly of descriptors which allow to accurately describe motions patterns and quantify gait semantics.

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