Movement Analysis in Learning by Repetitive Recall. An Approach for Automatic Assistance in Physiotherapy

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Abstract

This paper describes a method based on computer vision to analyze and compare patterns of people movements. An stochastic analysis of invariant algebraic moments from binarized image sequences of persons is proposed along with an approach for extracting frequency features from the time series obtained, in order to classify and categorize patients movements using a neural network. Based on studies of repetitive recall, an experiment with occupational therapy exercises was realized to classify the movement patterns performed by an hemiplegic patient to evaluate performance of the committed body part.

Keywords: *Movement analysis; Computer vision; Repetitive recall; Occupational therapy; Hemiplegia; Computer-assisted Physiotherapy.*

1 Introduction

In the human behavior analysis field, automatic identification of people movements represents a very broad research area worldwide. The initial state of the art has identified recent works that have been recognized, as mentioned in [4][6][7][8]. Initially, we studied methods to analyze people motion on video sequences. It was addressed the problem of extracting features from persons on images in different activities in time, such as walking, extending and retracting the arm, falling, etc., in order to apply it in the progress feedback for patients on physiotherapy. However, recent studies of neural enhancement and attenuation induced by repetitive recall [17][20] reported important knowledge about the neural activity during recall [22][23]. These studies allows extend research works focused on improving the effectiveness in the mobility maintenance process of patients with brain disorders like Spastic Cerebral Palsy type hemiplegia.

The first part of the article describes the set of input data, represented by binary images of patients movements. Subsequently, we present an approach used for features extraction from the captured images, based on Hu moments [13], and a stochastic analysis to validate them as a time series. Additionally, the extraction of frequency features from time series obtained is described, which conform patterns that will be trained by a neural network for a posterior movements classification. Finally, the proposed method is tested with an hemiplegic patient during an occupational therapy exercise, oriented to recreate the repetitive recall tests mentioned in [17], in order to study the movement performance during different kinds of therapy exercises.

Motivation

Studies based on functional Magnetic Resonance Imaging (fRMI), proposed by [17][20], provide new evidence that repeated cued recall is associated with changes in neural activities and support the hypothesis that repeated recall both attenuates and enhances neural activity in various brain regions. Thus, the findings indicate the possible neural underpinnings of the retrieval practice effect. The initial recall phase can provide additional encoding experience and strengthen the successful retrieval process [18]. Repeated retrieval might improve access to the encoded stimulus and/or reduce competition from other stimuli [19]. Results obtained in [17][20] allow to carry out studies related to neural activity, trying to get better results of driven processes not only for teaching-learning relationship, but also for medical areas that study the brain and its relationship with performs motor activities, especially in people with central nervous system disorders. The quantification and movement performance comparison could improve physiotherapy methods in order to reach a better impact in the mobility maintenance on hemiplegic patients, in terms of getting a faster and constant evolution on physical therapy, as well as allowing a more accuracy performance of activities and physiotherapeutic goals.

Problem description

The automatic identification and analysis of people movements is an active research area in video processing, which involves addressing of different subproblems such as image segmentation, where nowadays there are no unique solutions due to the variability of parameters that conforms a video scene. A unique solution would have difficulties adapting the segmentation parameters if the application goals differs. In order to get a more robust segmentation, we use a LIDAR sensor (Light Detection And Ranging, also LADAR) to incorporate complementary depth data. By the other hand, hemiplegia has well documented characteristics, with manifestations that vary depending on the patients and the treatment they are following, including an appropriate physiotherapy. However, there is little knowledge about the neurological effects of physiotherapy and its influence on motor skills in the short and long term. The most common method for evaluation in physiotherapy of upper body are based typically on effectiveness-efficiency observations, and not in quantitative references to evaluate more precisely the effects of therapy in patients, as in the case of GMFCS (Gross Motor Function Classification System)[2] or VGA (Video Gait Analysis)[3] to analyze the posture of the patient walking. More accurated methods for measuring specific body movements, involve the use of expensive equipments, increasing costs and treatment complexity. The present work propose a method based on computer vision to compare both approaches.

2 Methodology

The present work starts with image capturing, using a LIDAR sensor in order to improve the segmentation process. Algebraic moments [10][12] are used to extract features from binarized images, and has advantages with respect to geometric moments [1] given it characteristics of translation, scale and rotation invariances. This allows the extraction of representative images values for each position of the patient's movements. The stochastic analysis of invariant moments on image sequences aid to study the movement evolution *(figure 1)* and may complement methods for identifying displacement patterns that could be associated with human behavior. This approach allows us to express the image as a distribution function f defined by light intensity at coordinates x, y.

Figure 1.- Binary images of a patient in four instants of time.

This study analyzes binary images of patients, that is, contains only white pixels, where the patient is identified $f(x_p, y_p) = 1$, and black pixels to the bottom $f(x_f, y_f) = 0$. This representation facilitates the interpretation of geometric moments applied to grayscale images, defined as:

$$m_{pq} = \sum_{1}^{n_x} \sum_{1}^{n_x} x^p y^q f(x, y) \qquad (1)$$

Where m_{pq} represents the order of the moment $(p + q)$ of the intensity function $f(x, y)$. The geometric moments are often used to describe the object conformation in the image.

2.1 Hu Moments

The geometric moments [1] are good tools for image analysis, but usually in a video sequence the object of interest undergoes changes of scale, translation and rotation, and since geometric moments are directly related to the pixels position in the space, consequently the results are altered by such changes, which leads us to seek methods that allow us to study objects in a video sequence more reliably. However, there are methods which use mathematical invariant properties, mainly to translation, scaling and rotation. Such methods are known as algebraic moments [12]. The proposed work aims to analyze the algebraic Hu moments [13] from binary images of persons, and the goal is to study the temporal relationships of invariant moments [13][14] in patients on physiotherapy. Due to the properties and relative low computational cost, Hu moments are used in different applications such as [9], where is proposed an approach based on Hidden Markov Models on dynamic gesture recognition for human-machine interaction. Table 1 shows the first three Hu moments for the sequence of images in the figure 1. The data in the table 1 is part of a set of 79 invariant moments that were obtained from binary images, normalized and plotted in the figure 2 to display its temporal evolution.

Time	Hu 1	Hu 2	Hu 3
t = 1	0.00218876	0.00000367	0.0000000103
t = 2	0.00183761	0.00000150	0.0000001627
t = 3	0.00193297	0.00000212	0.0000001772
t = 4	0.00179688	0.00000190	0.0000000584

Table 1.- First three Hu moments from images in four instant of time.

Since we deal with Hu moments sequences as time series, it is appropriate to mention certain concepts that are related to this work and that will be determined by context, which leads us now to define a time series as any set of ordered observations in time. The approach for analyzing a time series can be considered in time-domain with parametric models and/or in frequency do-

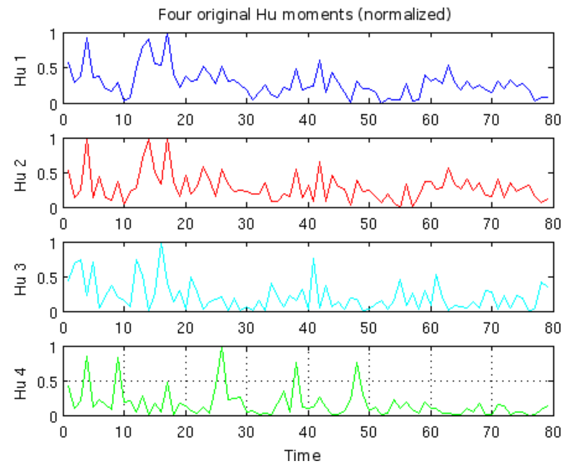

Figure 2.- First four Hu moments of 79 images from a patient movement

main with non-parametric models. For the case of our study, we wish to verify that the signal has a random component, which would lead us to consider the data set as a stochastic process [16], where X is a set of random variables defined on some space Ω:

$$(X_t, t \in [0, T]) = (X_t(\omega), t \in [0, T], \omega \in \Omega) \quad (2)$$

The set $[0, T]$ represent a group of infinite amount of time. The value of X in Eq. 2 is associated with the instant of time t and with the possible realizations ω. Thus, for a fixed time t the random variable is:

$$X_t = X_t(\omega), \omega \in \Omega \quad (3)$$

For a given state of $\omega \in \Omega$ nature, the random variable is a time function

$$X_t = X_t(\omega), t \in [0, T] \quad (4)$$

This function is called realization [16], trajectory or path of the process X. The stochastic process, as defined, introduces an important concept applied to signals with invariant features on temporal translation. A time series is called stationary if its statistical properties do not change with time. Temporal invariance in the strict sense, requires that the distribution function be identical at any instant of time, however, this property is hardly verifiable in practice. For this reason, for many applications it suffices to check that moments of the first and second order are invariant.

2.2 Analysis of Stationarity

As mentioned earlier, the approach to analyze a time series may be in the time domain, as well as in the frequency domain. We present an analysis considering both approaches, in order also to check the stationarity properties of the signal chosen.

Derivative's Method

The first approach to analyze the algebraic moments sequence considers the relationship between the monotony of a function $f(x)$ (increase or decrease) and the value of the first derivative $f'(x)$. This approach is known as first derivative criterion [5], which we apply to improve the signal conditions with respect to the mean.

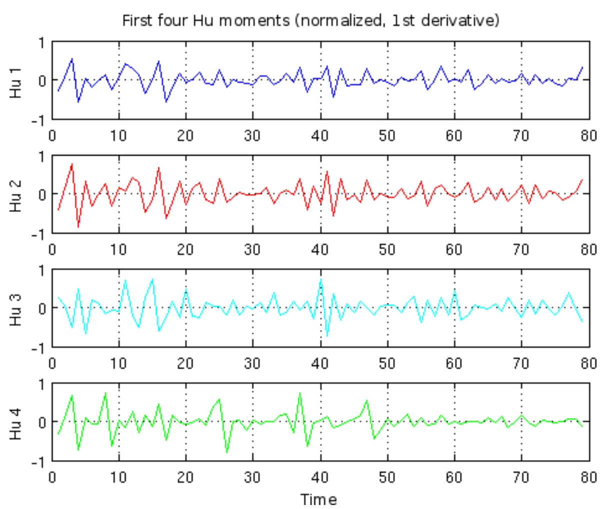

Figure 3.- First derivative of original sequence.

Figure 3 shows the Hu moments sequence in its first derivative. It's visually appreciable the signal correction respect to its mean, however, Figure 4 shows the PDFs (Probability Density Functions) of the first two Hu moments sequences, been possible to appreciate the tendency of average to be close to zero.

Temporal analysis

As explained above, the stationarity criterion implies invariance in time. We are going to take as reference the third Hu moment sequence for a time study. For this, the sequence will be divided into three intervals. Figure 5 shows the PDF(Probability Density Function) of two intervals. It's possible to appreciate the mean

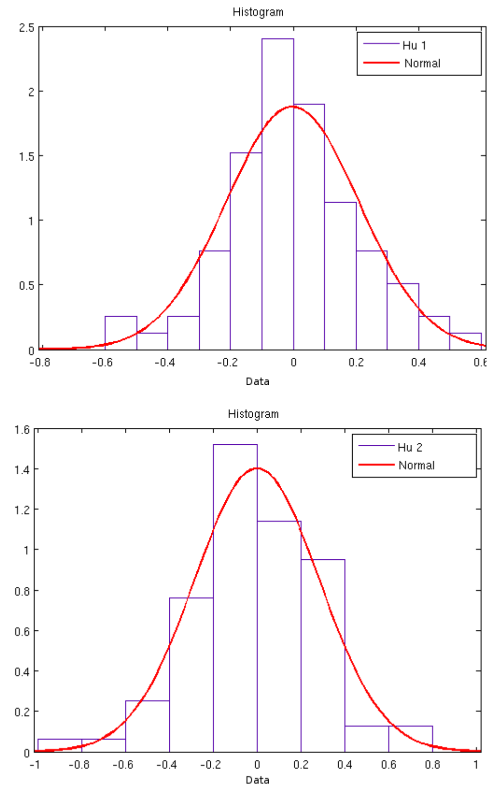

Figure 4.- PDF of sequence after first derivative; Moments Hu1 and Hu2.

tendency to be close to zero and the variance approximately constant *(Table 2)*.

	Interval 1	Interval 2	Interval 3
Mean	-0.03622205	-0.06076354	-0.05503439
Variance	0.10613619	0.06075918	0.04476413

Table 2.- Mean and Variance of three sequence intervals

Autocorrelation

Autocorrelation is a mathematical tool often used in signal processing. The autocorrelation function is defined as the signal cross-correlation with itself [11]. The autocorrelation function is very useful for finding repeating patterns in a signal. In statistics, the autocorrelation of a discrete series of a stationary process is no more than the correlation of the process with a time shifted version of itself. A second order stationary process with a core value μ, could be defined as:

$$R(k) = \frac{E[(X_i - \mu)(X_{i+k} - \mu)}{\sigma^2} \qquad (5)$$

where E is the expected value and k the temporal displacement. This function varies within the

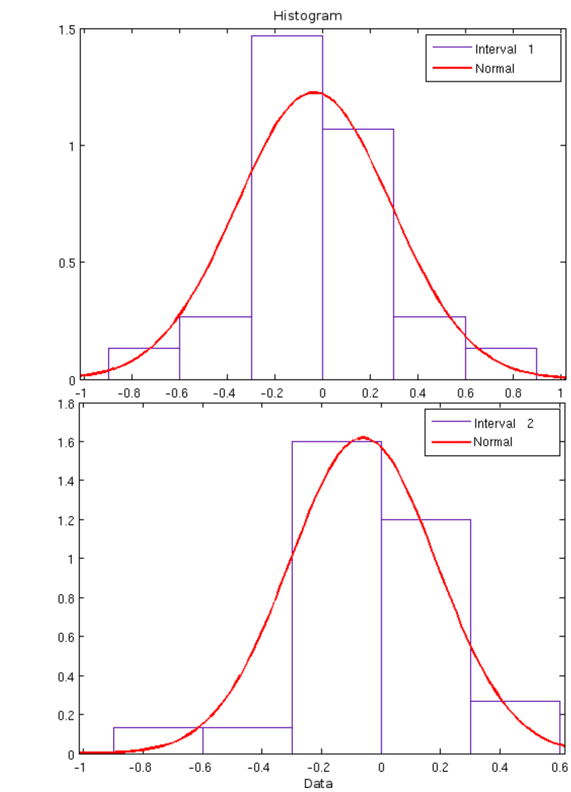

Figure 5.- PDF of third Hu moment sequence in two intervals

range $[-1, 1]$, where 1 indicates a perfect correlation (signal overlaps perfectly after a temporal displacement of k) and -1 indicates a perfect anti-correlation. It's a common practice to abandon the normalization by σ^2 *(eq.5)* and to use the autocorrelation and autocovariance interchangeably. The correlation analysis indicates the linear relationship between two variables, where the values are always between $+1$ and -1. The sign indicates the direction and if the correlation is positive or negative, and the size of the variable indicates the strength of the correlation. Figure 6 shows that autocorrelation remains near zero in each of three intervals selected, which is not only a sign of stationarity but also of decorrelation.

Frequency features extraction

Given the nature of human movements, it was considered a frequency analysis as a tool to facilitate the subsequent extraction of most representative features in the sequence of Hu moments. Through the Fourier transform (FFT) we are able to get the amplitude spectrum of each

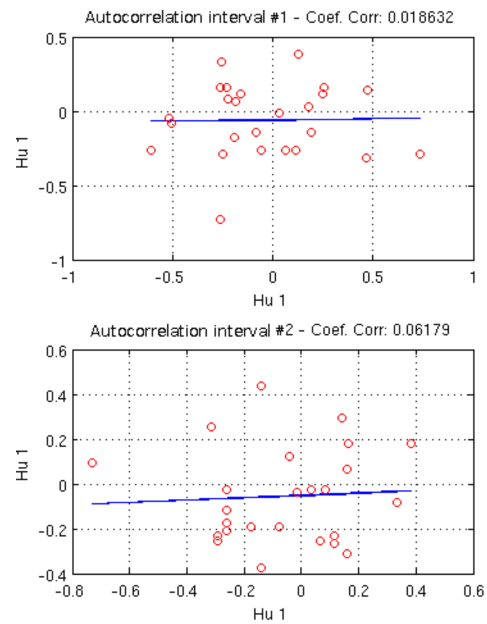

Figure 6.- 1st and 2nd Intervals autocorrelation; Hu1 moments sequence.

series, which has allowed an initial assessment of frequency behavior of the four sequences. This allowed a comparison with other temporal sequences obtained from different tests. After that, a Power Spectral Density was approximated by an autoregressive model, using an order 4 covariance method to highlight frequency features present in the signal. The model's order was determined after extraction and subsequent study of features, such as center frequency, average frequency, skewness coefficient and frequencies in the first and third quartile. Figure 7 shows the Power Density Spectrum of two Hu moments sequences.

3 Results

In the early stages of the research, several methods were studied to analyze patients movements on video sequences, specifically the problem of extracting invariant features from images of patients making different movements, describing the patient's body in a binary silhouette, as shown in figure 1. The features extraction, frequency analysis, relevance analysis and subsequent extraction and grouping, were applied to the image dataset, categorized by

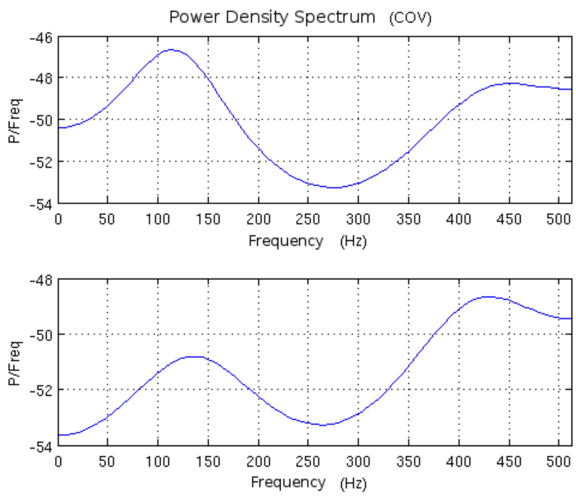

Figure 7.- 1st and 2nd Intervals autocorrelation; Hu1 moments sequence.

activity, in order to group patterns of each activity; in this case, extending and retracting the arm *(figure 1)* and other activities related to occupational therapy and repetitive recall [17], for subsequent classification using an optimized MLP (Multilayer Perceptron) neural network [15]. The method proposed was applied with an hemiplegic patient during the physiotherapy, and three different kind of movements were classified with mean of 96.72% (this value could change depending of the movement. Inertial sensors could be incorporated in a future work in order to reach a thinner classification). The patterns extracted of three moviments mencioned can be visualized in Figure 9.

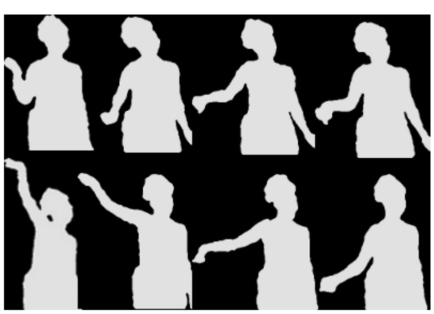

Figure 8.- Binary images in different instants of time during an up-middle-down identified moviment in a occupational therapy exercise.

The set of captured images allowed the identification of strategic movements that patient performs to achieve a goal, that strategic movement patterns as well as the goal movement pattern can be compared using the proposed method. Figure 9 shows three different movements patterns identified during an exercise of occupational therapy (stretching the arm, up-middle-down *(figure 8)* and making circles). The patterns in the figure 9 are frequency features extracted from Power Density Spectrum of each four Hu moments sequence from the captured images for each physiotherapy exercise.

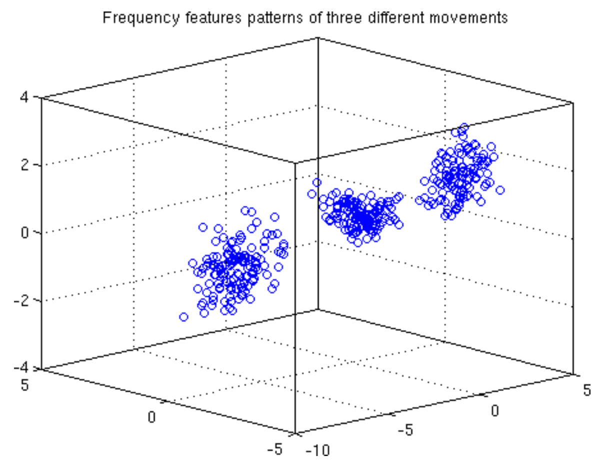

Figure 9.- Frequency features patterns of three different movements.

4 Conclusions

From the experimentation, we have observed that invariant moments of image sequences are good features to be analyzed given its stochastic properties for pattern recognition. The analysis of invariant moments sequences as temporal representatives of binarized patient's images, represent an interesting approach for addressing the problem of non-standard movement analysis. Considering studies about the positive influence of the recall process and the positive effect of occupational therapy, the methodology proposed could offer a non-expensive alternative to evaluate actual and new physiotherapy approaches based on patients movements performance, in order to improve the impact of physical therapy in terms of getting a faster and constant evolution for the patient, as well as allowing a more accurate performance of activities and physiotherapeutic goals.

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