Non-Intrusive Action Symmetry Measurement for Dementia and Rehabilitation

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Abstract

The purpose of this work is to quantify the symmetry in human actions, which is a common objective in medical research. To this end, a novel non-intrusive method for quantifying action symmetry in the frequency domain is proposed. Reflectional symmetry is estimated over time and a new metric is proposed based on dynamic symmetry warping distance. The proposed method can be utilised to provide quantitative estimates of symmetry in actions occurring during the examination of a patient. In order to evaluate the proposed approach and metric, experiments were performed both with phantom data where ground truth is available and with real data offering quantitative and qualitative analysis.

1 Introduction

The purpose of this work is to quantify the symmetry in human actions, which is a common objective in medical research. The symmetry between the sides of the human body can be a valuable metric for many medical related procedures and applications. For example, monitoring patients with cerebral palsy [9], in rehabilitation after a stroke [2] or amputation [10], diagnosis of Parkinson's disease in early stages [8] and even diagnosis of numerous medical conditions in infants [4].

There are four main categories of symmetry as described in the literature [5], (see figure 1). In research on human body motion analysis, the mirror-symmetry properties are examined, assuming that the axis of symmetry is vertical and the differences between the left and right side motions are considered. In existing literature on human body motion analysis, symmetry has been estimated using a variety of sensors all of which are intrusive to the subject. In particular, to acquire the measurements, a variety of sensors attached to the subjects have been employed (gyroscopes [3], accelerometers [6], motion capture sensors [14]). Additionally, the placement of the sensors and the acquisition of the respective measurements are not universal and they change according to the action or application.

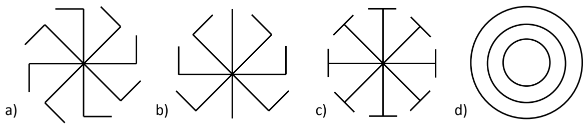

Figure 1: Examples of symmetry (a) rotational, (b) mirror, (c) radial and (d) circular.

To overcome the aforementioned limitations a computer vision approach is proposed to measure symmetry in humans actions. Finding symmetry in images is a well-studied subject. The symmetry detection task is performed either in the pixel [7] or in the frequency domain [12], with the Fourier techniques, that are based on Phase Correlation and log-polar transform to offer measurements with high degree of accuracy and robustness. This approach has the advantage of invariability to changes in illumination, is very fast, scale invariant and can estimate multiple symmetries simultaneously without additional computational cost, [12]. Furthermore, symmetry is an important feature in computer vision and is used for action classification [11].

In this work the concept of symmetry estimation over time with applications in the measurement of the progress of a patient during the rehabilitation or the diagnosis of Parkinson's and Alzheimer's disease is introduced.A novel, non-invasive, method is proposed to quantify symmetry in human actions using RGB or depth sequences. The technique of symmetry detection is extended to pairs of images. The contributions in this research are a novel method to estimate symmetry between a pair of images in the frequency domain and extending this approach to the time dimension by introducing a innovative Dynamic Symmetry Warping technique. The method introduced in this paper can quantify human action symmetry in a variety of cases where symmetry is an important feature for the monitoring of patients and the diagnosis of diseases.

2 Methodology

Initially, the subject is asked to perform some activities (e.g. flexion and extension of a limb) both from the left and the right side (see figure 2). The same activity is performed multiple times and then the captured data is pre-processed to extract the action silhouettes. The aim of the proposed algorithm is to estimate the level of symmetry between two actions. Initially symmetry in a single image is defined using properties in the Fourier domain. Next,the approach is extended to estimate the symmetry between a pair of images and finally temporal information is incorporated. As this research is aiming to identify symmetry between the left and the right side of the body, the main symmetry of the body is assumed to lie in the vertical axis of the image plane. The overall process is shown in figure 3.

2.1 Estimation of Reflectional Symmetry in the Frequency Domain

Working in the frequency domain allows the robust estimation of translation between images through phase correlation. Furthermore, it has been shown that after converting an image to polar coordinates the rotation can be measured as translation [13]. Exploiting this fact, the method proposed in [12] estimates the symmetry properties of images in the frequency domain, suggesting that the magnitude of the Fourier transform of the polar representation of an image can be used to obtain the symmetry properties of the image. The best approach to achieve a high quality polar representation is to use the fast and accurate polar Fourier transform proposed in [1]. This algorithm's computational complexity is the same order as the standard Cartesian Fast Fourier Transform (FFT), whilst the experimental results show

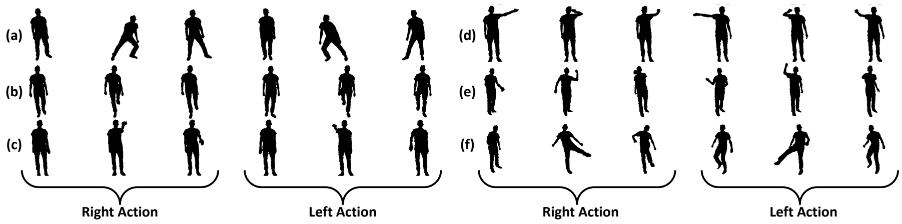

Figure 2: Examples of six symmetry actions performed by the patients in both sides.

high accuracy [1].

The aim is to identify reflectional symmetry in images. To this end symmetry detection is formulated in the frequency domain which enables the use of robust correlation-based techniques. The key advantage of a Fourier-based formulation is that for any type of symmetric pattern about a symmetry centre (x_0, y_0), the magnitude of its Fourier Transform is also symmetric about the origin $(0,0)$. This enables the computation of the axis of symmetry by a simple correlation in the polar domain. In particular, let denote by I a reflectionally symmetric image and let us also denote by a_0 the symmetry axis. Based on the Fourier properties, the magnitude M of Fourier Transform of I resampled on polar coordinates (r, θ) contains the information about the degree and the axis of symmetry that can be obtained by performing a 2D autocorrelation C, as shown below:

$$C = F^{-1}\{M \cdot M^*\} \tag{1}$$

where M is the Fourier transform of the polar magnitude, $*$ denotes the complex conjugate operator and F^{-1} denotes the inverse Fourier transform.

The higher the values in the output signal the higher the symmetry in the corresponding rotation, extrapolating this information allows the detection of the main axes of symmetry of the image as suggested in [12] and as shown can be used to quantify symmetry.

2.2 Symmetry Distance Metric

In order to evaluate and quantify the level of symmetry between two given images I_1 and I_2, a novel metric is proposed. According to the proposed approach, the two images are combined side by side into a larger image I, (see figure 3). Concatenating the images in this way ensures that the images found to be symmetrical also have a similar shape. Two dissimilar shapes may have the same symmetry properties but with the undertaken approach the dissimilarity in shape will result in asymmetry. Additionally, the main symmetry is forced to be near to the vertical axis so differences between the sides can be examined, which is the desired result.

After combining the images a 2D autocorrelation is performed on the polar Fourier transformed magnitude of the combined image I (equation (1)). Considering the highest peak in the output signal as the centre, dissimilarities either side suggest asymmetries between the images. The difference between the left (C_L) and the right side (C_R) of the signal is obtained by calculating their distance, as shown in equation (2):

$$S_D = \Delta(C_L, C_R) \tag{2}$$

where Δ is the Earth mover's distance (EMD) and is calculated by the following equation:

$$\Delta(C_L, C_R) = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} d_{ij} f_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} f_{ij}} \tag{3}$$

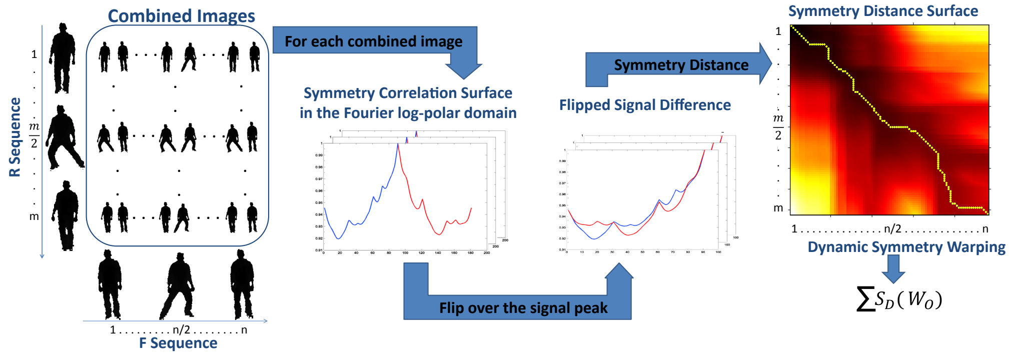

Figure 3: Each of the $m \times n$ combined images is represented in polar coordinates in the frequency domain and the magnitude is used for the 2D autocorrelation. The symmetry distance is calculated as the EMD of the sides of the correlation surface. The symmetry distance surface is composed of the symmetry distance of each combination of images while the index preserves the temporal structure of the original sequences. The yellow line represents the optimal path (w_o) that minimises the global symmetry distance between the two sequences.

where d denotes the ground distance between samples i and j along C_L and C_R and f the flow between them. According to the proposed metric, the smaller the symmetry distance S_D the higher is the symmetry between the images.

2.3 Dynamic Symmetry Warping

A symmetry detection and evaluation approach over time is introduced in this section allowing the quantitative assessment of action symmetry. In order to find the symmetry between two time series a novel approach based on the proposed symmetry distance metric is introduced. Dynamic Symmetry Warping (DSW) is a dynamic algorithm that computes the optimal symmetry between two sequences, by stretching the time dimension and summing the local symmetries of individual matched elements. The outputs of the DSW algorithm are the optimal warping of the sequences and the minimum global symmetry distance between the given series.

Specifically, each image of the sequence R, of length m, is combined with each image of the sequence F, of length n, and their symmetry distance is calculated as described in equation (2). The S_D values are arranged in an $m \times n$ symmetry distance surface matrix where the indices of m and n describe the temporal structure of R and F respectively. The warping path w that minimises the global symmetry distance G_W between the sequences, indicates the optimal global symmetry distance $G_S(R,F) = \min_w G_w(R,F)$ where G_w are the possible available paths of the accumulated symmetry distance surface:

$$G_w = \sum_{t=1}^{T} S_D(w_R(t)w_F(t)/N_w) \tag{4}$$

where N_w is a normalisation factor and

$$w_R(t) \in \{1...m\} \, and \, w_F(t) \in \{1...n\} \tag{5}$$

where $t = 1...T$, and T is the length of each path.

The normalisation factor N_w can be chosen according to the needs of the application, and determines the flexibility of the path selection. The output G_S is the optimal global symmetry difference between the image sequences after they are stretched in order to have the best possible symmetry. This metric can be used to assess symmetry in a variety of human actions and to assist the monitoring of patients and the diagnosis of diseases.

3 Results

In this section, the experiments performed and the results obtained are presented. In order to evaluate the proposed method, a new Action Symmetry Database (ASDB) was created that consists of both phantom and real data. The phantom dataset is a moving dummy where the main attributes of the motion for each case are known, providing ground truth for each case. The differentiated attributes are the speed and the angle of movement; and the shape of the limbs. Each one of the attributes is subjected to three variations: original state, 10% increment, and 20% increment, resulting in 27 different cases. The second part was captured with the Kinect sensor consisting of 5 subjects performing different actions, including: body weight shifting to each side, arm swings, leg swings, throwing a ball, kicking (see figure 2). Each person performs 6 actions and repeats each action 4 times on the right and 4 times on the left side.

The optimal global symmetry distance G_S metric is used to quantitatively evaluate our algorithm. For the experiments, the actions are considered pre-segmented, with each subject starting in a specific pose, performing an action and finishing in a specific pose. The normalisation factor that was used is $N = m + n$, providing a symmetric continuity constrain forcing each image to be matched at least once, even if that means that some images are matched more than once. In figure 4, the results for the phantom data are displayed, indicating that the proposed metrics are close to ground truth and follow the same trend since the values of our metric are increasing while we differentiate the motion attributes to induce asymmetry. The plots show the response of the system when we keep two parameters constant and increase the third. Also the variance is plotted to provide a more accurate representation of the performance of the proposed metrics. All the results are summarised in table 1.

Table 1: Phantom Data Estimated Mean Error and the Variance.

Angle Changes			Length Changes			Speed Changes		
0%	10%	20%	0%	10%	20%	0%	10%	20%
Length 0%			Angle 0%			Angle 0%		
0.336 (0.014)	1.462 (0.001)	3.03 (0.008)	0.336 (0.014)	2.227 (0.005)	4.686 (0.001)	2.345 (1.839)	2.433 (1.763)	2.471 (1.740)
Length 10%			Angle 10%			Angle 10%		
2.227 (0.005)	3.491 (0.002)	5.244 (0.012)	1.462 (0.001)	3.491 (0.002)	5.931 (0.005)	3.652 (1.851)	3.619 (1.816)	3.612 (1.814)
Length 20%			Angle 20%			Angle 20%		
4.686 (0.001)	5.930 (0.005)	7.738 (0.014)	3.03 (0.008)	5.244 (0.012)	7.738 (0.014)	5.448 (1.949)	5.331 (1.912)	5.234 (1.908)

Table 2: Real Data Estimated Mean Error and the Variance.

Actor	1	2	3	4	5	6
Symmetry	6.237 (1.167)	5.876 (1.563)	7.308 (1.101)	8.186 (2.549)	5.452 (1.562)	9.399 (3.004)

Regarding the real data the obtained results are shown in table 2. The more complex action of kicking (action 6) is scoring the highest value indicating that is performed the least symmetrical, as expected. The results show that the overall methodology provides an accurate non-intrusive action symmetry evaluation framework.

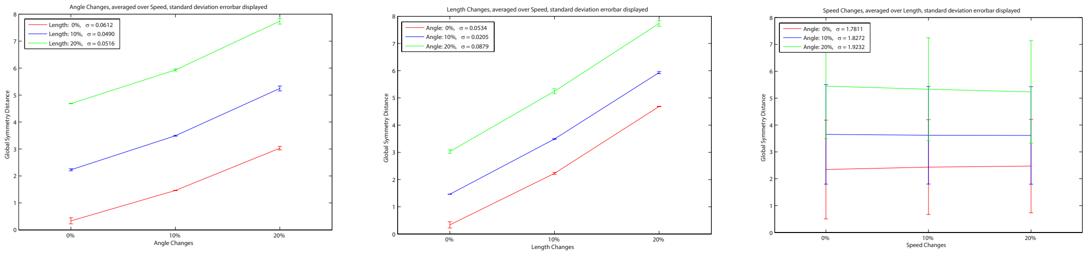

Figure 4: Obtained Action Symmetry Values for the phantom data using the proposed Symmetry Metric.

4 Discussion

In this paper a novel framework is proposed to detect and quantify symmetry between actions in a non-intrusive way. The suggested method operates in the frequency domain based on the properties of the Fourier transform. The proposed method has been quantitatively and qualitatively evaluated on the new Action Symmetry Database (ASDB) using both phantom and real samples.

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