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Extended summary

A markerless approach to human movement analysis

Curriculum: Elettromagnetismo e Bioingegneria

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Abstract. The aim of this PhD thesis was to derive a procedure able to estimate joint kinematics and the *Centre of Mass* (*CoM*) excursion, relative to a simple, yet functionally relevant, motor task using a markerless approach and computer graphic methods. The *Standing Reach (SR)* is the motor task analysed. A single webcam was placed orthogonally to the subject at 4 m distance. The frames were segmented by *Mixture of Gaussian (MoG)* method. The subject was modelled as a kinematic chain of 4 segments: foot, lower limb, trunk, and arm. The body segments have been approximated by ellipses using a *Discrete Curve Evolution algorithm (DCE)* and tracked among frames. The angles between body segments were calculated, compared with angular trajectories measured by electrogoniometers.

Results show the usefulness of the proposed approach in order to estimate joint kinematics in case of simple, mainly sagittal, motor tasks as *SR*.

Keywords. Anthropometric estimation, Human motion analysis, Markerless Analysis, Standing Reach.

1 Problem statement and objectives

1.1 Standing Reach analysis

Falls in the elderly represent a leading cause of disability, injury, and death. Identification of elderly people at high risk of falling should be a leading medical priority.

The postural control system deteriorates with age and disease, balance becomes increasingly tenuous resulting in an enhanced susceptibility to falls. It is important to be able to assess the subject's ability to maintain balance and to be able to predict the risk of falls.

In literature there are many clinical balance tests. *Standing reach (SR)* is the motor task analysed in this PhD thesis.

The motion is mainly confined to the sagittal plane. It consists in leaning the trunk forward trying to reach the maximum displacement of the arms, and maintaining the wrists at approximately the same height during the whole movement. The base of support is fixed during the task because the subject is required not to lift heels or to step forward. The maximum displacement of the arms is a measure of clinical significance for its predictive value about recurrent falls in the elderly subjects. Nevertheless, only this measure cannot be considered a measure of dynamic balance, in the sense that it is not able to differentiate healthy elders from individuals with balance impairments.

More insight can be obtained from the same motor task if it can be described, in an objective way, looking at its kinematic behaviour too.

2 Research planning and activities

For the characterization of the *SR* the following steps were performed:

2.1 Camera calibration

Camera calibration is necessary to obtain 3D information from 2D images of a scene. As a result of the calibration the intrinsic and extrinsic camera parameters are computed. The camera model used is the pinhole model.
A single webcam (resolution 640x480 pixels, 30 fps) was placed orthogonally to the subject's side and calibrated using the Zangh's method [1]. This technique only requires a planar pattern, similar to a checkerboard grid, to be placed at *n* different orientations (*n*>2) in front of the camera. The Zhang's method uses the extracted corner points of the checkerboard pattern to compute a projective transformation between the image points of the *n* different images, up to a scale factor.
An approximate solution of the intrinsic and extrinsic parameters is found, using a closed form solution. A refinement of the parameter estimates is obtained by a final non linear minimization of the retroprojection error, using a Levenberg-Marquardt method.

2.2 Background subtraction

Real-time segmentation of moving regions in image sequences is a fundamental step in many vision systems. A typical method is background subtraction. Many background models have been introduced to deal with different problems. One of the successful solutions to these problems is to use a background model per pixel proposed by Grimson *et al.* [2, 3, 4]. The authors introduce a method to model each background pixel by a mixture of *K* Gaussian distributions (*K* is a small number from 3 to 5). Each pixel in the scene is modelled by a mixture of *K* Gaussian distributions. The probability that a certain pixel has a value of X_N at time *N* can be written as

$$\left(X_n\right) = \sum_{j=1}^{K} w_j \cdot \eta\left(X_n;\theta_j\right) \tag{1}$$

where w_k is the weight parameter of the k^{th} Gaussian component, $\eta\left(X;\theta_k\right)$ is the Normal distribution of k^{th} component.
The *K* distributions are ordered based on the fitness value w_k/σ_k and the first *B* distributions are used as a model of the background of the scene, where *B* is estimated as

$$B = \arg\min_b\left(\sum_{j=1}^{b} w_j > T\right) \tag{2}$$

The threshold *T* is the minimum fraction of the background model. Background subtraction is performed by marking a foreground pixel any pixel that is more than 2.5 standard deviations away from any of the *B* distributions.

2.3 Body Approximation

The subject was modelled in the sagittal plane as a kinematic chain of 4 segments: foot, lower limb, trunk, and arm. The body segments have been approximated by ellipses and tracked using a *Discrete Curve Evolution (DCE)* algorithm.
The *DCE* method accomplishes this goal by simplifying the shape; it was introduced in [5, 6, 7]. In other word, given the input boundary polygon P with n vertices, *DCE* produces a sequence of simpler polygons $P = P^n P^{n-1} ... P^2$ such that $P^{n-(k+1)}$ is obtained by removing a single vertex *v* from P^{n-k} whose shape contribution measured by the functional K is the smallest. As a result of *DCE*, we obtain a subset of vertices that best represents the shape of a given contour. The difference between the original and the simplified contour is minimal. Therefore the subset of vertices is sufficient to study evolutions of polygonal shapes. The evolution of the polygon will be stopped when the simplified polygon P^{n-k} approximates the input contour suitably. A stop condition that is adequate for shape similarity is given for *DCE* in [8].
Applying, to each frame, the *DCE* algorithm we found the polygon vertices that best approximate of subject boundary. Each body segment was represented by ellipse equation that pass through the largtest number of these polygon vertices.

2.4 Parameters estimation

The *SR* kinematic analysis was performed considering the ankle angle (α), between the foot and lower limb, and the hip angle (β), between lower limb and trunk, Figure 1.
These angles were calculated using the automatic identification of the major axis of the ellipses associated with the relative body segments Figure 2.
The maximum displacement of the arms was determined as Euclidean distance between the final (last frame V_f) and the initial (first frame V_i) position of the distal vertex of the ellipse associated with the arm.

$$\Delta S_{\max} = \left\| V_f - V_i \right\| \tag{3}$$

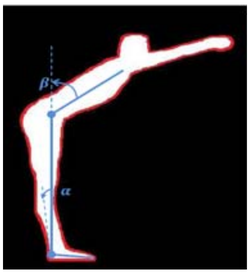

Figure 1: Definition of relative angles.

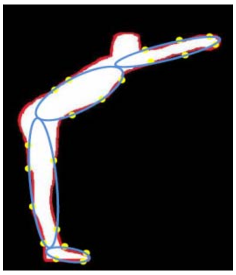

Figure 2: Approximation of body segments by ellipses.

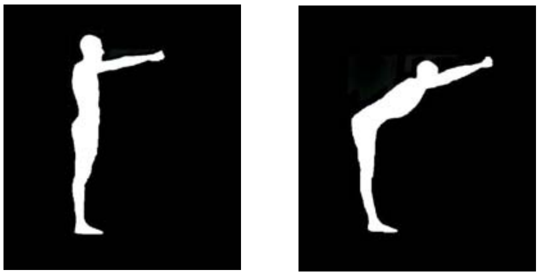

Figure 3: Segmentation of initial and final frame.

Moreover the *Centre of Mass (CoM)* excursion in the sagittal XY-plane was estimated as distance between the final (last frame $CoM_f = (x_f, y_f)$) and the initial (first frame) $CoM_i = (x_i, y_i)$ Position of ellipse centre associated with the trunk.

$$CoM_{AP} = x_f - x_i \tag{4}$$

$$CoM_{VERT} = y_f - y_i \tag{5}$$

and the *Anterior Limit of Stability (ASL)* was calculated as the maximum distance between the *CoM* projection on the base of support, X_{CoM},and the distal vertex of the ellipse that approximates the foot V_P:

$$\Delta_{ASL} = \| X_{CoM} - V_P \| \tag{6}$$

3 Analysis and discussion of main results

The whole procedure was tested on a young healthy subject. The execution time of *SR* was about 2 seconds, and the video sequence was composed by 54 frames. Applying the image segmentation was possible to discern the subject from background. Figure 3 shows the initial and final segmentation frames, obtained from threshold T and learning rate α_r (T=0,7 and α_r =0.005, respectively) that produce optimal segmentation. These values of T and α_r, was obtained by averaging values used on segmentation process of images in different light conditions.
For each frame wae identified the better polygonal that best approximates the boundary of the subject using the *DCE* algorithm. This step was computationally expensive, because the recursive algorithm convges in 10 second, for each frame.
The trajectories of α and β angles were obtained applying the estimation algorithm to all frames, during the *SR*. Figure 4 shows the estimated angles (α and β) between body segments, compared with angular trajectories measured by electrogoniometers.

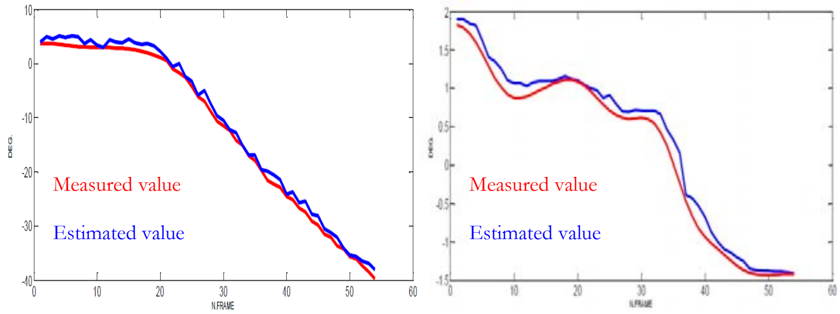

Figure 4: Angular trajectories (deg).

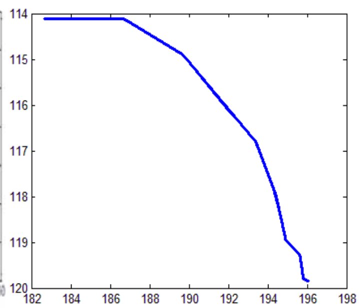

Figure 5: *CoM* trajectory in the frame reference system (pixel).

Finally, the following parameters were calculated:
1) The maximum displacement of the arms $\Delta S_{\max} = 38\ cm$
2) The *CoM* trajectory (Figure 5) and *CoM* excursion in the sagittal XY-plane
$CoM_{AP} = 12.1\ cm,\ CoM_{VERT} = 6.6\ cm$
3) The anterior limit of stability $\Delta_{ASL} = 4.8\ cm$.

4 Conclusions

The aim of this thesis was to implement a markerless algorithm to estimate the characteristic parameters of a motor task like SR that is significant in the context of functional evaluation of motor disorders and in particular of equilibrium.As working hypotheses was assumed: 1) the use of low cost instrumentation, 2) unstructured environment, 3) user friendliness of the whole tool in the sense that no specific technical skill is required for the end user; all these assumptions were completely satisfied.
The numerical results and the *CoM* trajectory confirm results found in literature though obtained here with a low cost instrumentation and a completely automatic procedure.
This PhD thesis is meant as a starting point for the markerless analysis of other significant motor tasks.
Future developments include a 3D application of the estimation algorithm and its use in clinical practice

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