HUMAN BODY TRACKING FOR PHYSIOTHERAPY VIRTUAL TRAINING

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Abstract: In this paper, we introduced a system in which it can be used for patients who are prescribed to undergo a physiotherapy treatment. In this personal virtual training system we employ several markers, attached to the various points of the human body. The system provides a physiotherapy session to the user, once the session is repeated by the user, the video image sequence captured by the system is analyzed and results are displayed to the user for further instructions. Our design consists of 3 general stages: detection, tracking, and verification stages. In the detection stage, our aim is to process the first frame of the image sequence for detecting the locations of the markers. In order to reduce the computational complexity of the first stage, the detection was performed in the lower scale of a Gaussian pyramid space representation. The second stage of our system performs tracking of detected markers of the first stage. A prediction algorithm is applied in this stage in order to limit the search along the predicted directions during the search for the markers in subsequent frames. For verification stage, the trajectory of the markers will be compared with the information in the model. Trajectory matching is performed by computing the difference between their smoothed zero-crossing potentials of the captured trajectory and the model.

1 INTRODUCTION

Human motion analysis by computer has become an important research issue in different areas of medicine and human science. In clinical gait analysis, for example, the temporal information about the position and orientation of the patient's joints may be useful in determining abnormalities (Yeasin ,2000). In orthopedics, the range of motion information helps in the evaluation of the prosthetic join replacement and physical therapy of joint disease (Richards,1999). Postural analysis during human motion can be studied from the representation of the column through the position of the markers fixed to the spinal process (Crosbie,1997). Athletic performance can also be improved by breaking down the movement into elementary components and by identifying suitable reference models arising from the observation of the outstanding athletes (Pedotti,1983).

For these reasons, there is a great interest in developing measurement techniques that allow a more accurate and automatic analysis of the human movement. In particular, systems based on markers and cameras, have been extensively used to record kinematics of the human motion (Richards,1999). Markers can be defined as special objects that are attached or fixed to the human body, helping to track the movement of important points.

In this paper, we present the design and implementation of a virtual personal physiotherapy trainer prototype using markers to improve the results. This system establishes a personalized physiotherapy session for the user and displays the resulting instruction on a monitor. The user periodically receives visual feedback from the virtual instructor on how he/she is currently doing. To accomplish this, we use a video camera in the room and incorporate various real-time computer vision techniques. Following presentation of a movement by an instructor, the patient repeats the movement accordingly. By capturing the video sequence of the trainee the task of the system is to recognize the physiotherapy movement of the user using the output of the vision system. In order to improve the performance of our system user needs to wear 12 markers. A cartoonish-like characters maybe used as the virtual instructors, but in this

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system we chose to use stored movie clips for simplicity. While we use only one instructor it might be more instructors involved. We currently have twelve physiotherapy moves used in our system.

Currently, a set of movie clips, showing a full view of the instructor, is used. In each clip the instructor performs a single cycle of the move then visual feedback of the instructor is displayed. In our proposed system if the algorithm recognizes that the user is performing the physiotherapy move correctly, it notifies the user that he performs complete movement correctly and if the user movement is wrong, system notifies the user that his movement is wrong and along with the information that which part of the body had wrong movement.

Our design is divided into the following three procedures: 1. Detection of the markers in the first frame. 2. Tracking markers in the rest of the frames and finding the trajectories 3. Matching motion trajectories with stored model.

The paper is organized as follows. In section 2 we introduce, without going into the details, the pervious systems related to human movement analysis. In Section 3 we described the method that was used for detection of markers in the first frame, and in Section 4 we explain how to track markers in a video sequence and this is divided into two procedures: matching and prediction. The matching is used to find correspondence between the extracted objects of two consecutive frames. The prediction stage is an important stage in order to limit the search region, thus reducing the execution time. In Section 5 the verification of the trajectories, recorded from markers movements, will be discussed and they are compared with the information for the models. Comparison between a trajectory and the model is performed by computing the difference between their smoothed zero-crossing potentials. Our experimental results are in Section 6 and conclusion is in Section 7.

2 PREVIOUS SYSTEM

A system called W4 (Haritaoglu,1998) is a real time visual surveillance system for detecting and tracking people and monitoring their activities in an outdoor environment. It operates on monocular grayscale video imagery, or on video imagery from an infrared camera.

Other system called Pfinder (Wren ,1997) is a real-time system for tracking a person which it uses a multi-class statistical model of color and shape to segment a person from a background scene. It finds and tracks people’s head and hands under a wide range of viewing condition.

System introduced by Kidrooms (Bobick,1996) is a tracking system based on “closed-world regions”. These are regions of space and time in which the specific context of what is in the regions is assumed to be known. These regions are tracked in real-time domains where object motions are not smooth or rigid, and where multiple objects are interacting.

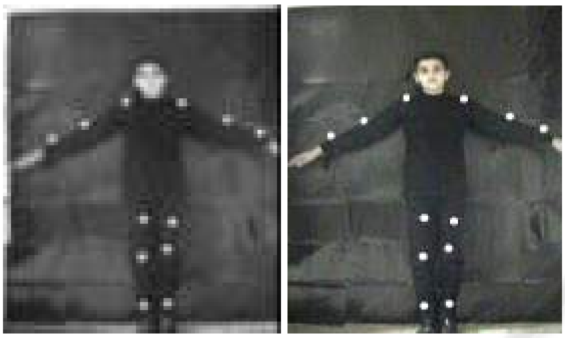
3 DETECTION

As mentioned earlier, there are 12 markers; as shown in Figure 2; these are used to locate important human body points. Detection of markers in the first frame is an important step in our proposed system. We used a Gaussian Pyramid representation in order to decrease computational processing time. Each level of a Gaussian pyramid is a lower resolution with respect to the previous one. In each level we simply performed two operations: 1) low-pass filter of the image, and 2) discarding the odd numbered rows and columns from the filtered image. These operations performed for both of input image and template image. Low-pass filtering of input image is accomplished by taking a weighted average of a 5x5 region surrounding at each image pixel. To increase computation efficiency, a separable equivalent weighting function was used to perform the 5x5 weighted averages. At first, convolving an image with a 1x5 weighting function, the 'horizontal' weighted average of the image is obtained. Next, convolving the horizontally averaged result with the transpose of the 1x5 vector (i.e. a '5x1') weighting function results the 'vertical' weighted averaging. A Gaussian-like weighting function with values of [.05 .25 .5 .25 .05] was used as the impulse response of our filter. Due to our input image frame size, we used the two-level pyramid in our system. As an example, a frame of video sequence in the original size and its lower resolution is shown in the Figure 2.

Once the resolution of an image and the template is decreased, using Gaussian pyramid at one level, then a template representing a marker must be searched in the lower level. When located, then we find the probable locations of the markers within the 2x2 region surrounding the places found in the corresponding locations of the original image. The cross-correlation function is used for detection, given by the following relationship.

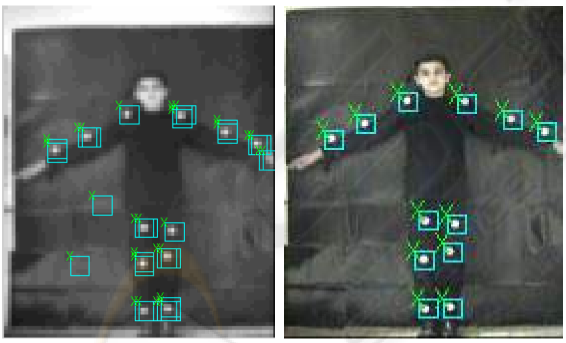
$$C_{ij} = \frac{\sum_{m=-M}^{M}\sum_{n=-N}^{N}(f(i+m,j+n)-\bar{f}(i,j))(h(m,n)-\bar{h})}{\sqrt{\sum_{m=-M}^{M}\sum_{n=-N}^{N}(f(i+m,j+n)-\bar{f}(i,j))^2}\sqrt{\sum_{m=-M}^{M}\sum_{n=-N}^{N}(h(m,n)-\bar{h})^2}} \quad (1)$$

where C_{ij} is the cross correlation value at (i,j)th location between function *f(,)*, the color image for original image and gray image for lower level image in the searched region, and *h(,)*, the model of the marker with (2M+1)× (2N+1) pixels. The values $\bar{f}$ and $\bar{h}$ are the mean of *f* and *h*, respectively. In Figure 3, detection of markers in one of our experiments at low and high resolutions is shown.



(a) (b)

Figure 2: (a) lower resolution (b) Original image.



(a) (b)

Figure 3: (a) marker found in lower resolution (b) Location of marker found at original image shown with squares.

4 TRACKING

Tracking the motion of human's parts, in a sequence of images, is an important step in automatic analysis of the human movement. This is a challenging problem due to non-rigidity of the human body, the influence of the environment, and other constraints. The automatic tracking can be used in a variety of applications, such as clinical gait analysis improvement of the human performance in sports, ergonomics, and so on. This involve in two parts, matching and prediction.

4.1 Matching

Matching is referred to as steps necessary to find the correspondence of markers between 2 consecutive frames. The matching between a marker model and its corresponding within an image is based on the gray-scale values of the pixels and it is evaluated by the Mean Absolute Difference (MAD) function between the marker model and a portion of the image within the search region. The template matching is accomplished by locating the points where MAD between the image and the model is minimized. In this way, the computation complexity is highly reduced. The MAD at (i, j)th location is defined as

$$D_{ij} = \sum_{m=-M}^{M}\sum_{n=-N}^{N}(|\, f(i+m,j+n) - h(m,n)\,|) , (2)$$

Where *f* is input image within the search area and *h* is the pixel value of the model representing the marker of size (2M+1)× (2N+1) pixels. The location with minimum value is location of marker.

4.2 Prediction

The matching function is applied to the significant regions extracted from the segmentation algorithm in the prediction step. This local aspect reduces the processing time of the matching step. Of course, regions with high correlations are selected corresponding to the expected position of the markers.

In order to reduce the search region, it is necessary to define a mechanism to predict the possible positions of the markers at the successive frames. For this purpose, we can use a simple extrapolation function. This can be done by a rough prediction, according to the following extrapolation function:

$$x_c = \frac{1}{3}(7x_k - 5x_{k-1} + x_{k-2})$$

$$y_c = \frac{1}{3}(7y_k - 5y_{k-1} + y_{k-2}), \quad (3)$$

where x_k and y_k are the spatial location of the current markers point for the *k*th frame, and x_c, y_c represent the center of the searching region for the *(k+1)*th frame, after finding x_c, y_c We searched region around x_c, y_c with radius 7 pixel for finding marker. In fact region size for markers searching is 15*15 pixels. We determined this region size from several experiments.

Figure 4 : Trajectory of motion after tracking.

5 VERIFICATION OF MOTION

5.1 Smoothing Trajectory

A trajectory is a spatio-temporal curve defined as: (x[1],y[1], 1), (x[2], y[2], 2),…, (x[n], y[n], n) where x[n],y[n] are coordinate value of a marker in frame n. There are essentially two 1-D functions involved: x[n] and y[n] in the above definition of a trajectory. A trajectory for a specific action performed in one of our demonstration is shown in the Figure 4 and its temporal function is shown in Figure 5b. This trajectory contains some noise due to errors during tracking. In order to deal with this noise, we use a Gaussian kernel as defined below, and apply it to the noisy signal to smooth x[n] and y[n] coordinates of the trajectory. We convolve trajectory with Gaussian kernel described by equation given below. For our experiments s =2 was selected. Result of smoothing is shown in the Figure 5a.

$$G^s(x) = \frac{1}{(s\sqrt{2\pi})} \exp(-\frac{\|x\|^2}{2s^2}) \qquad (4)$$

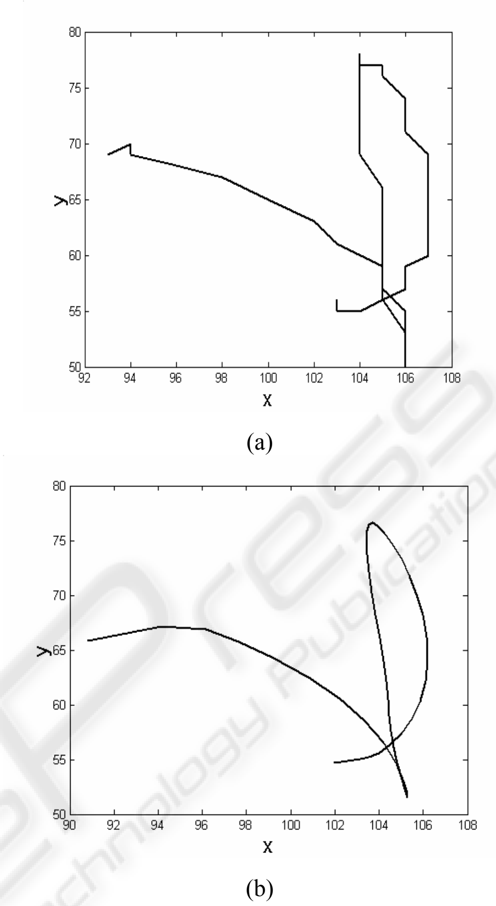


Figure 5 : (a) noisy trajectory of marker (b) Smoothed trajectory of marker.

5.2 Spatio-temporal Curvature Parameterization

We use spatio-temporal curvature (Cedras, 1995) to represent an action. In this case, a 1D version of a quadratic surface fitting procedure is used. The spatio-temporal curvature, represented by *k,* is computed as follows:

$$k = \frac{\sqrt{A^2 + B^2 + C^2}}{((x')^2 + (y')^2 + (z')^2)^{3/2}}, \qquad (5)$$

Where

$$A = \begin{vmatrix} y' & t' \\ y'' & t'' \end{vmatrix}, B = \begin{vmatrix} t' & x' \\ t'' & x'' \end{vmatrix}, C = \begin{vmatrix} x' & y' \\ x'' & y'' \end{vmatrix}$$

where the notation $|\cdot|$ represents the determinant of a matrix. The first and second derivative of a function *x(t)* is denoted by $x'(t) = x(t) - x(t-1)$,

$x''(t) = x'(t) - x'(t-1)$, respectively. Since the time interval is constant, so $t' = 1$, and $t'' = 0$.

The spatio-temporal curvature has the advantage over other trajectory parameterizations since it captures both the speed and direction changes in one quantity. Figure 6 depicts the spatio-temporal curvature for a trajectory as captured from Figure 5.

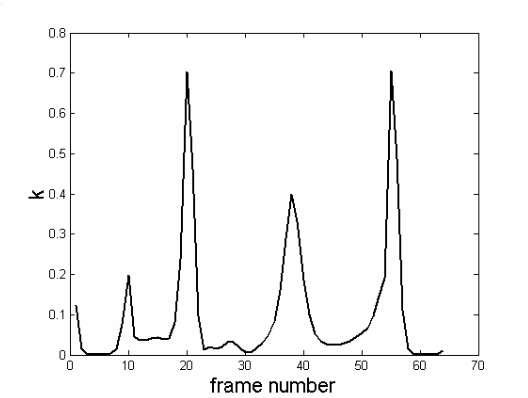


Figure 6: Spatio-temporal curvature for trajectory Figure 5.

5.3 Matching Trajectory

There are twelve trajectories related to the twelve markers which will be compared with the stored information of the model. A match score for each marker is produced which indicates how closely the two trajectories matched.

Matching between two trajectories is evaluated by computing the difference between their smoothed zero-crossing potentials, and employing the idea of (Rangarajan,1993) for matching the scale-space representation. The first step in this algorithm is to decompose the trajectory into 1D signal, the spatio-temporal curvature that was explained in the pervious section. The scale-space is computed by repeatedly convolving the input spatio-temporal curvature signal with second derivative of Gaussian mask with various σ values. The output is then checked for zero-crossings, the indicative of discontinuities. The location and potential (the absolute difference between the values where the zero-crossing occurs) of each zero-crossing is stored in a set of arrays, one for each σ value. The set of arrays is organized into a two dimensional table, with the location (frame number) as the x axis and σ as the y axis. It is well known that the zero-crossings of a distorted signal are dislocalized and as a result, the zero-crossing potentials from a distorted signal are not the same as those from an undistorted signal. However, a smoothed zero-crossing potential is less sensitive to noise, so the zero-crossing from that table are diffused by convolving with a two dimensional Gaussian of standard deviation equal to 1 (see figure 7). In the next step, this array is multiplied by a scaling factor and the results are stored as an array. The matching itself is done by element by element subtraction operations between the diffused input and the model in the scale-spaces representation. The absolute values from the subtraction are stored. In the final step, the match score is computed using the following equation:

$$match \quad score = 1 - \frac{\sum\sum|\varepsilon_k(n,\sigma)|}{2*\sum\sum|\alpha_k(n,\sigma)|} \qquad (6)$$

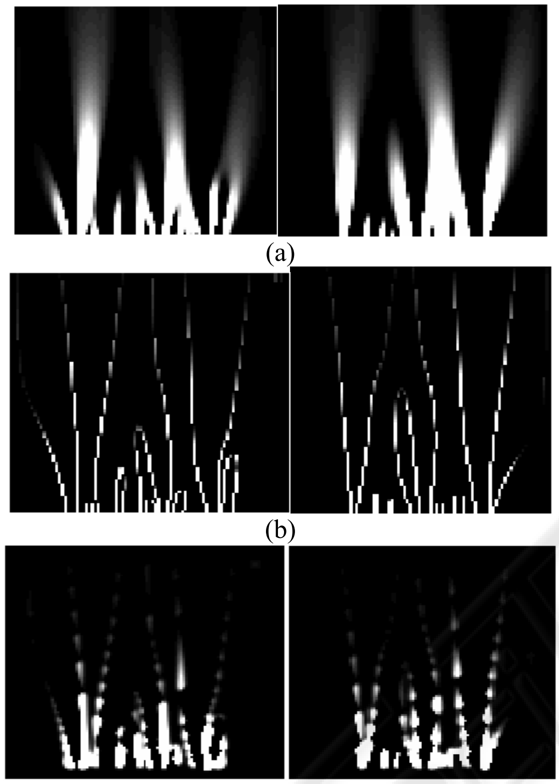
where ε_k is the array containing the element by element subtraction of input and model, for spatio-temporal curvature and α_k represent spatio-temporal curvature of the model. If this score is lower than the preset threshold, we used a value of 0.7 for the threshold, then the user's motion is wrong, otherwise it is right. The user is notified due to the wrong joint movements.

6 EXPERIMENTS

Images of our video sequences are 144x176 pixels in size. We have considered twelve different physiotherapy actions performed by a user, and we have recorded a large number of video sequences. In Figure 8 we have shown a few frames from only 2 different moves. We have considered cases where the markers may come very close to each other; even in some cases we had overlaps between the markers. We also tested the system under different speed of body movements. Results of detection and tracking in all actions were performed correctly and there were no errors in the verification of all twelve movements. Figure 8 shows sequences of two actions. Our overall evaluation will be completed once the system is tested with complex movements.

7 CONCLUSIONS

In this work, we introduced a system for a virtual personal physiotherapy trainer. One of the main advantages of this system is its comfort and possibility of using it in personal environment for training physiotherapy movement where the therapists is not available or patient may be at remote area in which the expert is not readily accessible. The important feature of the system is its precision, and furthermore, if the user's movement is wrong, the system would notify the user of the error and advise the patient, that which part of the movement was wrong.

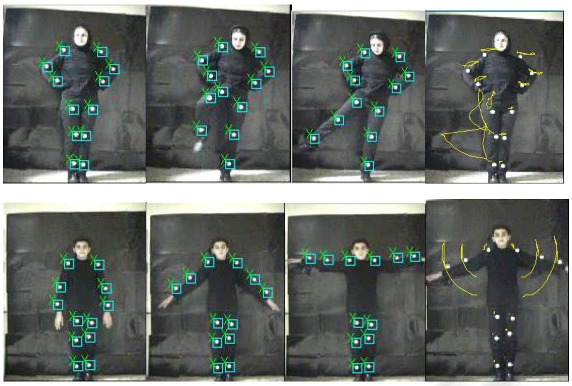


(a)

(b)

(c)

Figure 7: (a) Scale-space of spatio-temporal of trajectory a sample and reference motion (b) Zero-crossing potential of the spatio-temporal curvature scale-space of trajectory a sample and reference motion (c) The diffused zero-crossing potential of the spatio-temporal curvature scale-space of trajectory a sample and reference motion.



(a) (b) (c) (d)

Figure 8 : video sequences of four actions .There are 60 frames in each sequence . (a) frame 1 (b) frame 10 (c) frame 40 (d) trajectory of markers.

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