A Neural Network for Moving Light Display Trajectory Prediction

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Abstract

In this paper, a radial basis function (rbf) neural network is trained to estimate the positions of markers placed on the joints of a subject. The network was also used to predict the positions of markers that were self-occluded. Results shows that using rbf in this application is successful.

1 Introduction

Moving Light Displays (MLDs) are image sequences containing only selected points of a 3-D object in each frame. This technique has been used for studying human motion by placing passive markers or light bulbs on the joints of a subject – see fig.1. MLDs are also used for studying human motion perception, subject recognition and for human gait analysis, see for example, [4], [6] and [1], respectively.

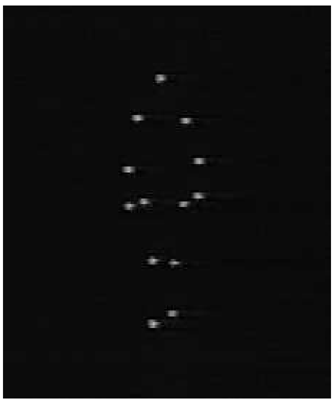

Figure 1: A single frame of a walker having MLDs on joints – front view

A computer system has been built for recognising walking persons based on MLD sequences [5]. As shown in fig. 2, in some frames one or more markers may be hidden behind another part of the body. Self occlusion makes it difficult to correctly plot the trajectories of the motion of a joint and hence correctly analyse gait.

In gait analysis labs where one cannot afford to miss the location of a marker at any instant, the problem of self-occlusion is overcome by placing a number of cameras – four or five – in such a way that at each instant each marker is seen by at least two cameras, which is evidently an expensive way to solve the problem.

In [7], Taylor et al present an extrapolation technique based on a 2-D linear least squares approximation to predict the the position of each joint/marker in the frame and use a nearest neighbour criterion to choose among different possibilities if more than one marker is in the neighbourhood of the predicted position.

In this paper, we propose a neural network trained to predict the position of the joint markers at different instants.

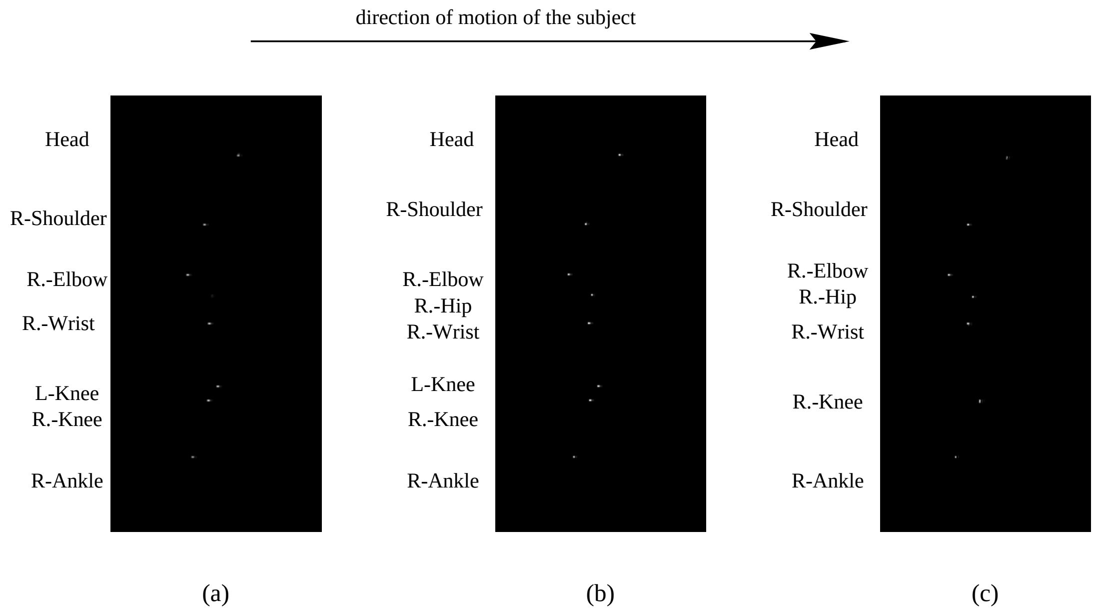

Figure 2: a sequence of frames of a walker having MLDs on joints – side view (sagittal plane)– showing self-occlusions (a) arm occludes the right hip marker (b) hip and knee markers are visible (c) left knee marker is occluded

2 Algorithm

In the algorithm we present in this paper, a radial basis function neural network [2], [3] is trained to do the interpolation between the successive frames and use the trained network for predicting the positions of self-occluded markers.

A pair of networks is trained for each joint – one for the x- and one for the y-coordinate motion. The inputs to the network are the time and the corresponding relative coordinates of the joint in a sequence of frames (coordinates are measured relative to a fixed marker on the body of the subject, e.g. shoulder marker).

Several walks are recorded for the subject while walking at his/her normal speed. The training data of the network consists of a set of coordinates of the marker of a particular joint and the corresponding time of several gait cycles from different walks. A gait cycle is defined as the time interval between two successive occurrences of one of the repetitive events of walking, e.g. between two right-heel strikes [8]. The testing data is a new set of coordinates in other gait cycles that has missing joint coordinates in one or more of the frames and it is the network's job to predict the position of the joint under consideration.

3 Results

A radial basis function network was trained to find the best fit of the trajectory for each marker. The trained network was used to predict the coordinates of the joint marker. Some points were intentionally occluded to test the robustness of the algorithm. The mean squared error (MSE) between the actual locations and the predicted position is calculated.

Figure 3 shows the results of a typical experiment predicting the location of the hip marker which was occasionally occluded due to the arm movement in the sagittal (side view) plane. The positions of the markers at ~ 70 % and ~ 80 % of the gait cycle were intentionally occluded, yet as shown in the figure the network managed to predict the positions of x- and the y-coordinate with only one pixel difference – *average* Relative Error for the x-coordinate $= 7.56 \times 10^{-3}$ % and *average* Relative Error for y-coordinate $= 2.37 \times 10^{-3}$ %. The network was trained by 15 cycles and was tested by 10 cycles.

Other networks for predicting the location of the rest of the markers for both side view and frontal view were also trained and tested and showed similar results.

4 Conclusion

In this paper, we have shown that the use of radial basis function neural network is a promising method for prediction positions of joints of a walking subject and hence it can be used to estimate the positions of joints that are self-occluded during motion.

Acknowledgement

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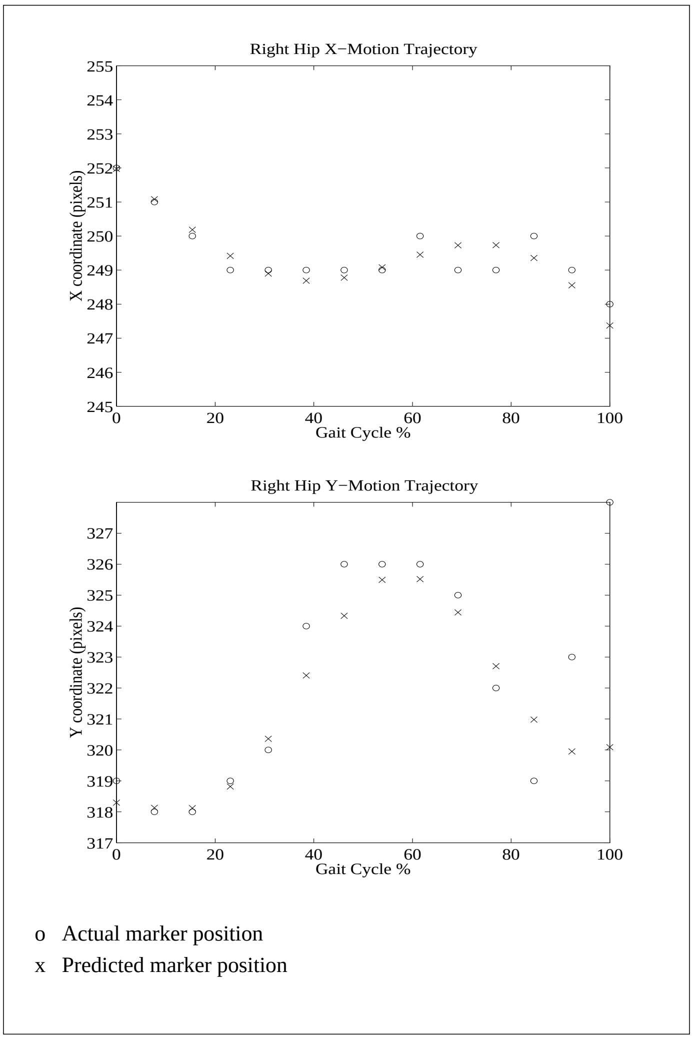

Figure 3: Actual and predicted positions of the right hip marker of a walking subject

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