Fast Human Motion Tracking by using High Speed Neural Networks

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Abstract: In this paper, we present fast neural networks (FNNs) for human motion detection, which might be advantageous especially in various tasks of image tracking. The proposed FNNs uses cross correlation in the frequency domain between the input image and the input weights of neural networks. It is proved mathematically and practically that the number of computation steps required for the FNNs is less than that needed by conventional neural Networks (CNNs). Simulation results using MATLAB confirm the theoretical computations. Then, another neural networks to classify human motion activities (e.g. walking, running) is used. To eliminate the undesirable problems accompanying human motion such as lighting and objects, we adapt and efficiently adapt existing techniques ranging from homomorphic filtering to simple morphological operations. Moreover, an intelligent technique to optimize the process of the moving target, by significantly reducing the number of pixels using the "star" skeletonization is introduced. With this approach, no more than eleven Fourier descriptors are required to completely describe the moving target. The approach is computationally inexpensive and thus ideal for video applications including video surveillance. An experiment to certify this efficiency was performed with 100 % accuracy results.

Keywords: Cross Correlation, Frequency Domain, Fast Neural Network, Computer Vision, Filter, Motion Detection, Image skeletonization, Feature extraction, Fourier descriptor,.

1. Introduction

Human motion activity is currently one of the most active research topics in computer vision [1-3]. This strong interest is driven by the wide spectrum of promising applications in many areas such as virtual reality, smart surveillance and perceptual-interface [4-5]. These activities are described by analyzing or classifying the motion of human target in a video stream. One of the most active area is activity understanding from video imagery. Understanding activities involve being able to detect and classify targets of interest and analyze what they are doing. Human motion classification is one such research area [6-8]. Moreover, in recent years the research activities in the area of machine vision have been intensified further as the result of its applications being extended toward video representation and coding purpose [9-10]. There are a number of approaches involving shape, motion, and statistical analysis proposed over the years. However, the relatively new approach of using color information has gained increasing attention in recent time. Some recent publications that have reported this study include [11-13]. In [14-15], the authors discuss the effect of camera, light-setting human race and color spaces has in the process.

Here, the work presented in [26] is modified and developed. This paper presents fast algorithms for human motion detection and then classification by using high speed neural networks The homomorphic filter and simple morphological operations has been suggested to overcome the problems of lighting and other moving objects around the target. The broad internal motion features of a target using the star skeletonization procedure is extracted. These features are reduced to eleven samples using Fourier transformation. Finally, the Fourier descriptors are fed to neural network to classify the motion of human as walking or running. This paper is organized as follows: Section 2 describes how the adaptation of the Homomorphic filter. Section 3 introduce the extraction of the moving targets. The data reduction technique is described in section 4. Section 5 proposes the features extraction of the target. Section 6 presents the neural network classification. The new approach of fast human motion detection is presented in section 7. Experimental results are descibed in section 8. Finally, the conclusions are presented in section 9.

2. Homomorphic Filtering

It is important to emphasize the existence of different difficulties and problems in the environment surrounding the moving target. Among problems we cite, for instance, the slow moving of other objects than the target, and the slow changing of lighting. With the aim to master such difficulties, we resorted to the filtering and morphological operations of the image. The filter technique proposed in this paper is homomorphic filtering [16-17]. The general idea of homomorphic filtering is shown in figure 1. The image frame I_t is first passed through a logarithmic non-linearity that provides dynamic range compression. It is then Fourier transformed, and its representation in the spatial frequency domain is modified by applying a filter that provides image enhancement. The modified image is then inverse Fourier transformed and is passes through an exponential non-linearity that reverses the effects of the logarithmic nonlinearity by the following:

$$S_i(x,y) = \ln[I_i(x,y)] \qquad (1)$$

$$S'(v,w) = F(S_i(x,y)] \qquad (2)$$

$$S_i''(v,w) = S'(v,w)H(v,w) \qquad (3)$$

$$S_i'''(x,y) = F^{-1}[S_i''(v,w)] \qquad (4)$$

$$I_i'(x,y) = \exp[S_i'''(x,y)] \qquad (5)$$

Where F, and F^{-1} represent the Fourier and the inverse Fourier transforms respectively, and H represents the homomorphic filter. It is in its final exponential transform that the homomorphic used to go back to the original domain.

3. Pre-Processing

The initial stage of the human motion problem after Homomorphic filtering is the extraction of moving target from a video stream. The approach is inspired by a region- based features, presented in [18], and is extracted from preprocessed binary map. These binary maps can be represented the image of the moving and non-moving areas of the sequences, as seen in figure 2 and figure 3 where moving areas are highlighted in black. The motion is extracted by pixel - wise differencing of consecutive frames given by :

$$O_1(t)=I_t(x, y)-I_b(x,y) \begin{cases} 1 & > \text{threshold} \\ 0 & < \text{threshold} \end{cases} \qquad (6)$$

Where $O_1(t)$ is the Euclidean between color image pixels in consecutive frames I_t and background frame $I_{b,}$ and x, y represent the pixel location. Therefore this paper performs simple morphological operations such as dilation to fill in any small hole in the target area and erosion to remove any small object in the background area as shown in figure 3.

4. Data Reduction

The internal motion of the moving target is the change in its boundary shape over time and a good way to quantify this is to use skeletonization. The method used here provides a simple robust way of detecting external point on the boundary of the target to produce a "star skeleton". The star skeleton consists of only the gross extremities of the target joined to its centroid in a "star" fashion. There are many advantages of this type of skeletonization process. It is not iterative, is therefore computationally cheap, and it also provides a mechanism for controlling scale sensitivity. Finally it relies on no a priori human model.

1- The contour boundary of the target can be extracted using Freeman code chain [19]: an 8-directional code describing the direction of each path segment. The codes and the contour image are shown in figure (4).

2- The centroid of the target image boundary (x_c,y_c) is determined by

$$x_c = \frac{1}{Nb}\sum_{i=1}^{Nb} x_i \ , \ y_c = \frac{1}{Nb}\sum_{i=1}^{Nb} y_i \qquad (7)$$

where (x_c,y_c) is the average contour boundary pixel position, N_b is the number of contour boundary pixels, and (x_i,y_i) is a pixel on the boundary of the target.

3- The distance di from the centroid (x_c,y_c) to each border point (x_i,y_i) are calculated as:

$$d_i = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \qquad (8)$$

4- Local maxima of d_i are taken as external points and the star skeleton is constructed by connecting them to the target centroid (x_c,y_c) [20]. Figure 5 show the steps of data reduction and figure 6 show the construction of the star skeleton.

5. Features Extraction

For the case in which a human is moving in an upright position, it can be assumed that the lower external points are legs, so choosing these as points to cyclic motion seems a reasonable approach. In particular, the left –most lower external point (L_x,L_y) is used as the cyclic point. Note that this choice does not guarantee that the feature is being performed on the same physical leg such as a right /left leg at all times. However, it is not necessary that the same leg are detected at all times, because the cyclic structure of the motion will still be evident from this point's motion. Then, the angle (L_x,L_y) makes with vertical θ is calculated as:

$$\theta = \tan^{-1} \frac{Lx - Xc}{Ly - Yc} \qquad (9)$$

Figure 7 shows the definition of (L_x,L_y) and θ. The motion features θ are fed to the fast Fourier transform to reduce the data. The eleven Fourier descriptors are used to represent the human motion. Finally, the Fourier descriptors are used to fed to the neural network. Artificial neural network is employed to classify the human motion activities such as walking or running.

6. Classification Technique

Artificial neural network (ANN) are highly parallel information processing systems resembling that of human brain configured in regular architectures. The collective behavior demonstrates the ability to learn, recall and generalize from training patterns or data. A neural network learns about its environment through an iterative process of adjustments applied to its synaptic weights and thresholds. Ideally, the network becomes more knowledgeable about its environment after each iteration of the learning process. Learning can be defined as a process by which the free parameters of a neural network are adapted through the a continuing process of simulation by the

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environment in which the network is embedded. Because of their learning and memorizing capability, a neural network classifier is used to classify the human motion behavior [21-22]. The proposed methodology model is a classifier. The standard back propagation network using feed forward topology and supervised learning is selected, which recorded good results in the different classification applications. MATLAB neural network toolbox is used as an effective software in implementing and training neural networks. Once the model and the architecture are selected the training phase begin.. For faster training the train gradient with momentum and adaptive learning rate algorithm "traingdx", an already existing algorithm in the MATLAB software, is used.

7. Fast Motion Detection by using High Speed Neural Networks

First neural networks are trained to classify sub-images which contain human motion from those which do not and this is done in the spatial domain. In the test phase, each sub-image in the input image (under test) is tested for the presence or absence of human motion. At each pixel position in the input image each sub-image is multiplied by a window of weights, which has the same size as the sub-image. This multiplication is done in the spatial domain. The outputs of neurons in the hidden layer are multiplied by the weights of the output layer. When the final output is high this means that the sub-image under test contain human motion and vice versa. Thus, we may conclude that this searching problem is cross correlation in the spatial domain between the image under test and the input weights of neural networks.

In this section, a fast algorithm for detecting human motion based on two dimensional cross correlations that take place between the tested image and the sliding window (20x20 pixels) is described. Such window is represented by the neural network weights situated between the input unit and the hidden layer. The convolution theorem in mathematical analysis says that a convolution of *f* with *h* is identical to the result of the following steps: let *F* and *H* be the results of the Fourier transformation of f and h in the frequency domain. Multiply *F* and *H* in the frequency domain point by point and then transform this product into spatial domain via the inverse Fourier transform [27-91]. As a result, these cross correlations can be represented by a product in the frequency domain. Thus, by using cross correlation in the frequency domain a speed up in an order of magnitude can be achieved during the detection process [27-91].

In the detection phase, a sub-image X of size *mxz* (sliding window) is extracted from the tested image, which has a size PxT, and fed to the neural network. Let W_i be the vector of weights between the input sub-image and the hidden layer. This vector has a size of *mxz* and can be represented as *mxz* matrix. The output of hidden neurons h_i can be calculated as follows:

$$h_i = g\left(\sum_{j=1}^{m} \sum_{k=1}^{z} W_i(j,k) X(j,k) + b_i \right) \quad (10)$$

where g is the activation function and b_i is the bias of each hidden neuron *(i)*. Eq.2 represents the output of each hidden neuron for a particular sub-image *I*. It can be computed for the whole image Ψ as follows:

$$h_i(u,v) = g\left(\sum_{j=-m/2}^{m/2} \sum_{k=-z/2}^{z/2} W_i(j,k)\Psi(u+j, v+k) + b_i \right) \quad (11)$$

Eq.(11) represents a cross correlation operation. Given any two functions *f* and *g*, their cross correlation can be obtained by [23]:

$$g(x,y) \otimes f(x,y) = \left(\sum_{m=-\infty}^{\infty} \sum_{z=-\infty}^{\infty} g(m,z) f(x+m, y+z) \right) \quad (12)$$

Therefore, Eq.(12) can be written as follows [23]:

$$h_i = g\left(W_i \otimes \Psi + b_i\right) \quad (13)$$

where h_i is the output of the hidden neuron *(i)* and $h_i\ (u,v)$ is the activity of the hidden unit *(i)* when the sliding window is located at position *(u,v)* in the input image Ψ and $(u,v) \in [P-m+1, T-n+1]$.
Now, the above cross correlation can be expressed in terms of the Fourier Transform:

$$W_i \otimes \Psi = F^{-1}\left(F(\Psi) \bullet F^*\left(W_i\right)\right) \quad (14)$$

(*) means the conjugate of the *FFT* for the weight matrix. Hence, by evaluating this cross correlation, a speed up ratio can be obtained comparable to conventional neural networks. Also, the final output of the neural network can be evaluated as follows:

$$O(u,v) = g\left(\sum_{i=1}^{q} W_o(i)\, h_i(u,v) + b_o \right) \quad (15)$$

where q is the number of neurons in the hidden layer. $O(u,v)$ is the output of the neural network when the sliding window located at the position (u,v) in the input image Ψ. W_o is the weight matrix between hidden and output layer.

The complexity of cross correlation in the frequency domain can be analyzed as follows:

1. For a tested image of NxN pixels, the *2D-FFT* requires a number equal to $N^2 log_2 N^2$ of complex computation steps. Also, the same number of complex computation steps is required for computing the *2D-FFT* of the weight matrix for each neuron in the hidden layer.

2. At each neuron in the hidden layer, the inverse *2D-FFT* is computed. So, q backward and $(1+q)$ forward transforms have to be computed. Therefore, for an image under test, the total number of the *2D-FFT* to compute is $(2q+1)N^2 log_2 N^2$.

3. The input image and the weights should be multiplied in the frequency domain. Therefore, a number of complex computation steps equal to qN^2 should be added.

4. The number of computation steps required by the fast neural networks is complex and must be converted into a real version. It is known that the two dimensional Fast Fourier Transform requires $(N^2/2)log_2 N^2$ complex multiplications and $N^2 log_2 N^2$ complex additions [24]. Every complex multiplication is realized by six real floating point operations and every complex addition is implemented by two real floating point operations. So, the total number of computation steps required to obtain the *2D-FFT* of an *NxN* image is:

$$\rho = 6((N^2/2)log_2 N^2) + 2(N^2 log_2 N^2) \quad (16)$$

which may be simplified to:

$$\rho = 5N^2 log_2 N^2 \quad (17)$$

Performing complex dot product in the frequency domain also requires $6qN^2$ real operations.

5. In order to perform cross correlation in the frequency domain, the weight matrix must have the same size as the input image. Assume that the input object has a size of (nxn) dimensions. So, the search process will be done over sub-images of (nxn) dimensions and the weight matrix will have the same size. Therefore, a number of zeros = (N^2-n^2) must be added to the weight matrix. This requires a total real number of computation steps = $q(N^2-n^2)$ for all neurons. Moreover, after computing the

2D-FFT for the weight matrix, the conjugate of this matrix must be obtained. So, a real number of computation steps $=qN^2$ should be added in order to obtain the conjugate of the weight matrix for all neurons. Also, a number of real computation steps equal to N is required to create butterflies complex numbers $(e^{-jk(2\Pi n/N)})$, where $0<K<L$. These $(N/2)$ complex numbers are multiplied by the elements of the input image or by previous complex numbers during the computation of the *2D-FFT*. To create a complex number requires two real floating point operations. So, the total number of computation steps required for the fast neural networks becomes:

$$\sigma=(2q+1)(5N^2 log_2 N^2) +6qN^2+q(N^2-^2)+qN^2 +N \quad (18)$$

which can be reformulated as:

$$\sigma=(2q+1)(5N^2 log_2 N^2) +q(8N^2-n^2) +N \quad (19)$$

6. Using a sliding window of size nxn for the same image of *NxN* pixels, $q(2n^2-1)(N-n+1)^2$ computation steps are required when using traditional neural networks for object detection process. The theoretical speed up factor η can be evaluated as follows:

$$\eta = \frac{q(2n^2 - 1)(N - n + 1)^2}{(2q+1)(5N^2 log_2 N^2) + q(8N^2 - n^2) + N} \quad (20)$$

8. Experimental Results

The theoretical speed up ratio Eq. 20 with different sizes of the input image and different in size weight matrices is listed in Table 1. Practical speed up ratio for manipulating images of different sizes and different in size weight matrices is listed in Table 2 using 2.7 GHz processor and *MATLAB ver 5.3*. An interesting property with FNNs is that the number of computation steps does not depend on either the size of the input sub-image or the size of the weight matrix (n). The effect of (n) on the number of computation steps is very small and can be ignored. This is in contrast to CNNs in which the number of computation steps is increased with the size of both the input sub-image and the weight matrix (n).

After detection, the experiments were carried out on a database of 15 different image sequences. All the sequences are approximately 20 second long and captured at 25 frame per second given a total of 7500 frames which amounts to approximately 5 minutes. The sequences are full 24-bit color and have a resolution of 240 by 320 pixels. The human motion was detected using the methods described in preprocessing technique as shown in figure (3). The chain code of the target is used to analyze the human motion as shown in figure (4). This paper presents the approach of star skeletonization to extract the feature of cyclic motion using Fourier descriptors as shown in figures (5,6,7 and 8). Finally, Neural Network is used to classify human motion such as walking or running.

Figure (9,10-a) shows twenty frames of human running and walking respectively. An example of border contours of human walking are shown in figure(10- b) and the angle θ between two legs are shown in figure (11). Figure(12) show an example of the normalized Fourier descriptors of human walk and run of figure(9) and figure (10) respectively. Finally the neural network classification perform an efficiency with 100 % accuracy results.

9. Conclusion

A new fast algorithm for human motion tracking has been presented. This has been achieved by performing cross correlation in the frequency domain between input image and the input weights of fast neural networks (FNNs). It has been proved mathematically and practically that the number of computation steps required for the presented FNNs is less than that needed by conventional neural networks (CNNs). Simulation results using MATLAB has confirmed the theoretical computations. In addition, the human movements analysis using neural network have been introduced. The novelty of this algorithm combines both roboust and fast features extraction. The existing techniques have been efficiently adapted ranging from homomorphic filtering to simple morphological operations. With this new approach, no more than eleven Fourier descriptors are required to completely describe the moving target. The approach is computationally inexpensive and thus ideal for video applications including video surveillance. An experiment to certify this efficiency was performed with 100 % accuracy results. In the future, this analysis technique will be applied to more complex human motions such as crawling, jumping, and so on.

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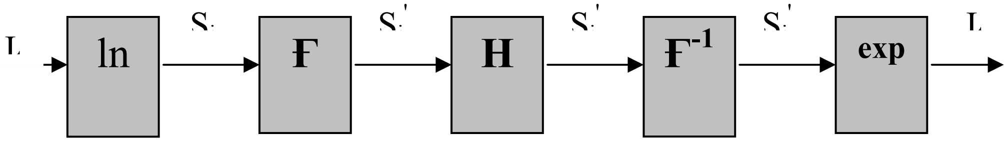

Figure 1: Homomorphic filtering.

Figure 2:a) The Original Image

Figure 2:b) The Background Image

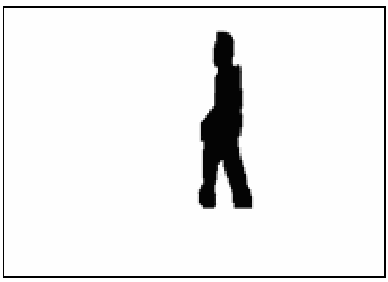

Figure 3: The Output Binary Bitmap Image After Dilation and Erosion

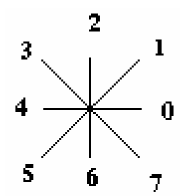

Figure 4: Freeman chain code

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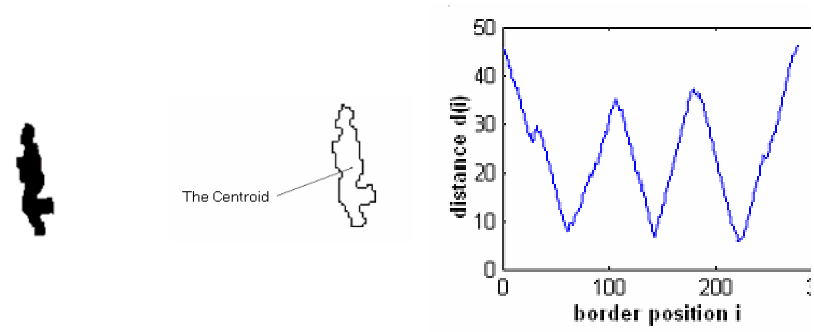


(a) (b) (c)

Figure 5: a) Binary Image b) The contour and the centroid point c) Boundary as a distance function.

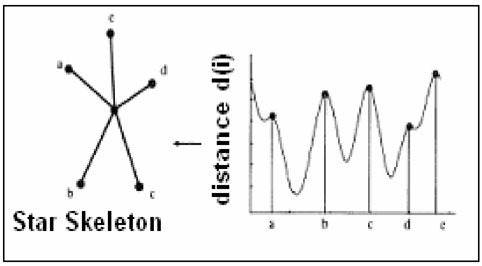
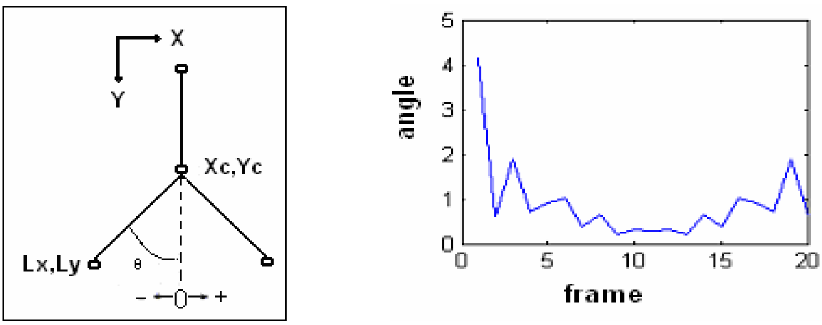


Figure 6: Star skeleton



(a) (b)

Figure 7. a) The Skeleton Definition b) The Motion Feature (θ).

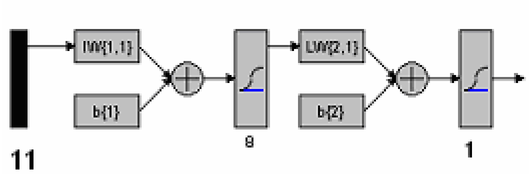


Figure 8. The neural network used for classification.

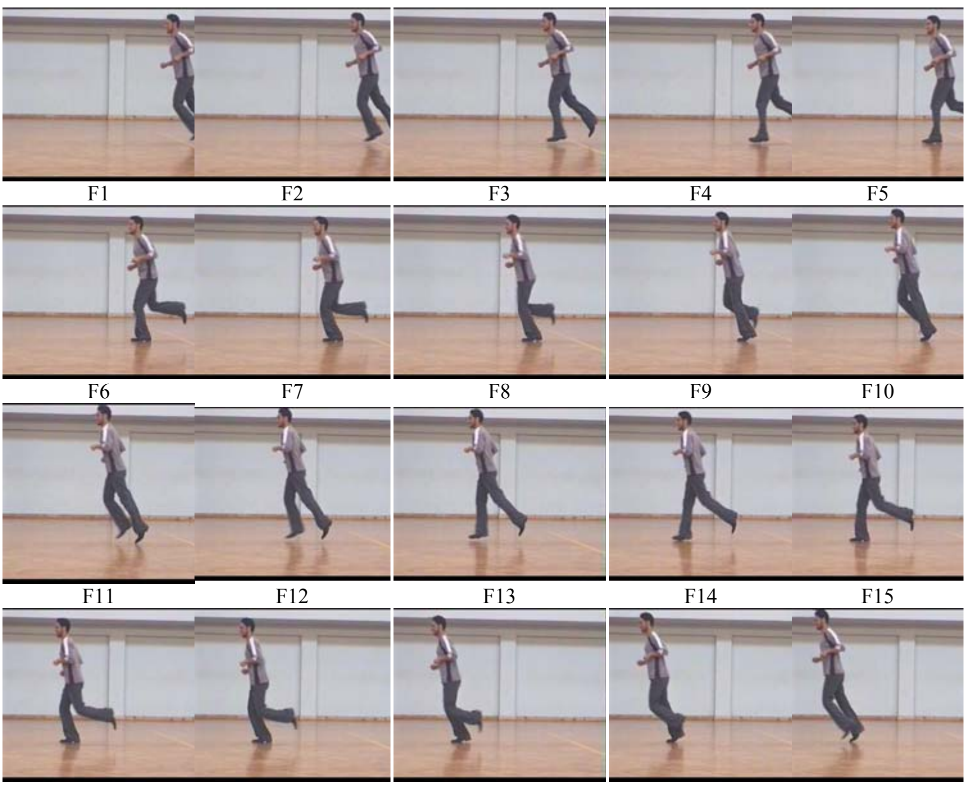


Figure 9: human running example

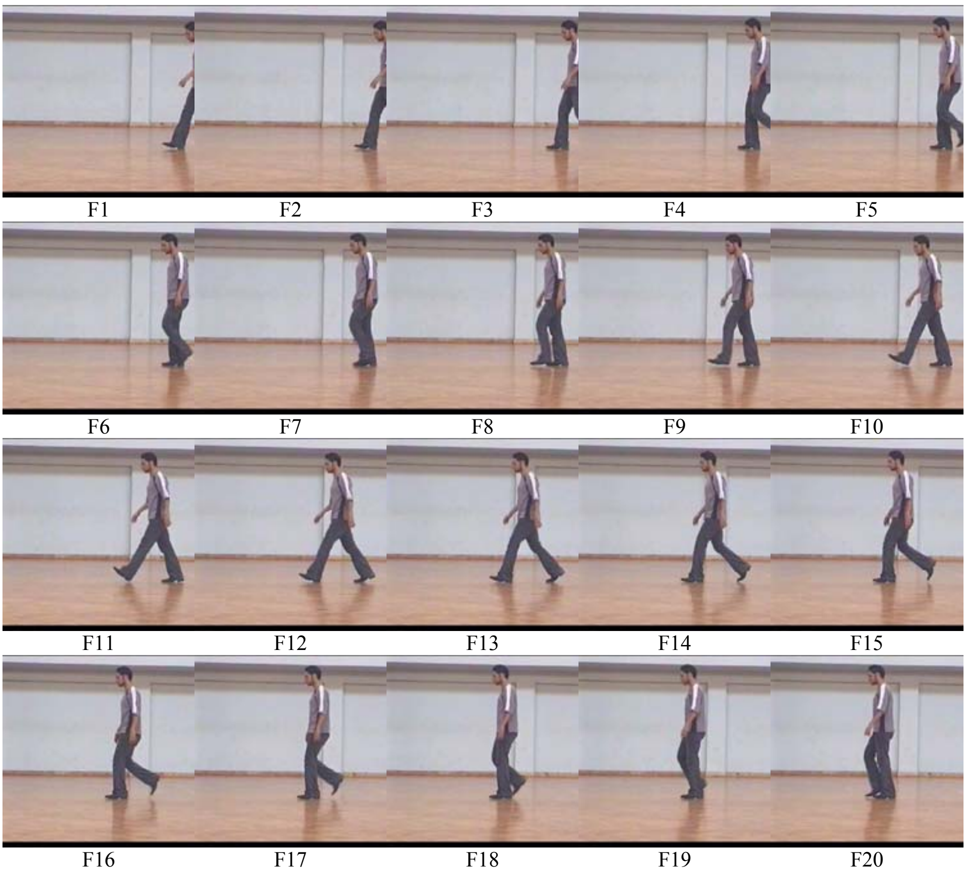


Figure 10:a) human motion example

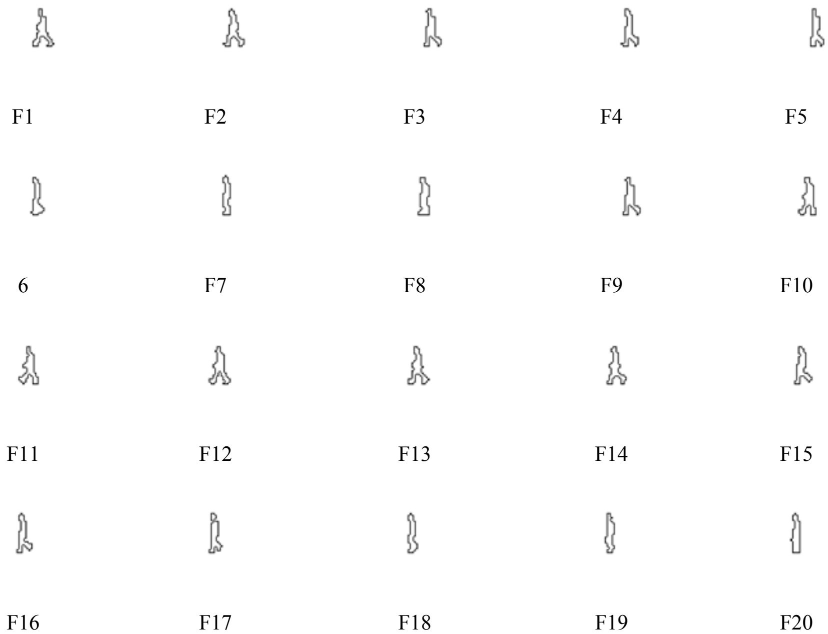


Figure 10:b) The contour extraction of human Walking

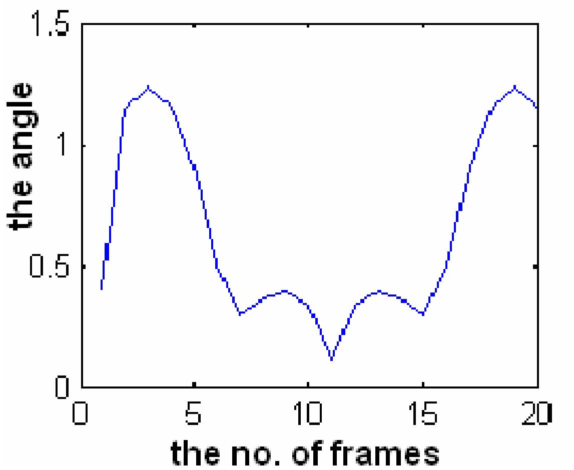


Figure 11: The angle plot for human walk

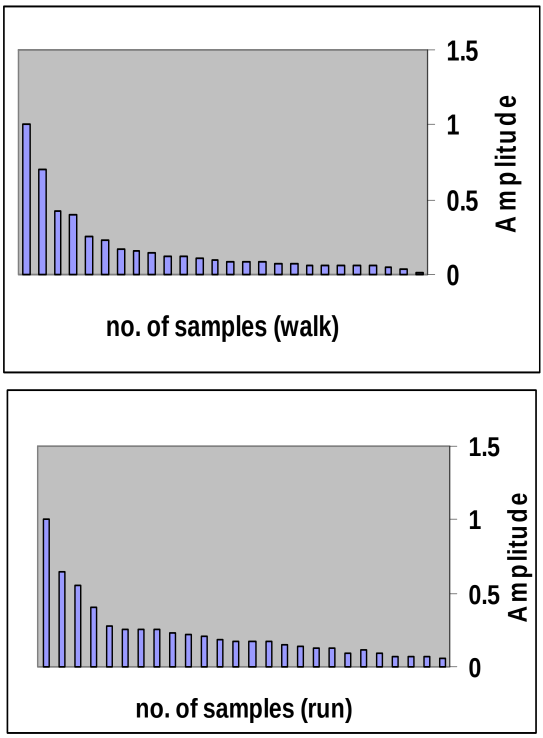


Figure 12: The Fourier Descriptors of Human motion

Table 1: The theoretical speed up ratio of human motion detection for images with different sizes.

Image size	Speed up ratio (n=20)	Speed up ratio (n=25)	Speed up ratio (n=30)
100x100	3.67	5.04	6.34
200x200	4.01	5.92	8.05
300x300	4.00	6.03	8.37
400x400	3.95	6.01	8.42
500x500	3.89	5.95	8.39
600x600	3.83	5.88	8.33
700x700	3.78	5.82	8.26
800x800	3.73	5.76	8.19
900x900	3.69	5.70	8.12
1000x1000	3.65	5.65	8.05
1100x1100	3.62	5.60	7.99
1200x1200	3.58	5.55	7.93
1300x1300	3.55	5.51	7.93
1400x1400	3.53	5.47	7.82
1500x1500	3.50	5.43	7.77
1600x1600	3.48	5.43	7.72
1700x1700	3.45	5.37	7.68
1800x1800	3.43	5.34	7.64
1900x1900	3.41	5.31	7.60
2000x2000	3.40	5.28	7.56

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Table 2: Practical speed up ratio of human motion detection for images with different sizes using MATLAB Ver 5.3.

Image size	Speed up ratio (n=20)	Speed up ratio (n=25)	Speed up ratio (n=30)
100x100	7.88	10.75	14.69
200x200	6.21	9.19	13.17
300x300	5.54	8.43	12.21
400x400	4.78	7.45	11.41
500x500	4.68	7.13	10.79
600x600	4.46	6.97	10.28
700x700	4.34	6.83	9.81
800x800	4.27	6.68	9.60
900x900	4.31	6.79	9.72
1000x1000	4.19	6.59	9.46
1100x1100	4.24	6.66	9.62
1200x1200	4.20	6.62	9.57
1300x1300	4.17	6.57	9.53
1400x1400	4.13	6.53	9.49
1500x1500	4.10	6.49	9.45
1600x1600	4.07	6.45	9.41
1700x1700	4.03	6.41	9.37
1800x1800	4.00	6.38	9.32
1900x1900	3.97	6.35	9.28
2000x2000	3.94	6.31	9.25