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A Comprehensive Investigation of Muscle Activations and Contractions for Behavioural Trait Detection through Human-Gait using Soft-Computing Technique

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Abstract

In the present research work a thorough investigation of muscle activation and contraction has been done for the detection of behavioural traits through human-gait images. Considerable amount of features have been extracted and relevant parameters have been computed for such investigation and a vast corpus of data sets have been developed. The data sets consist of a features and computed parameters extracted from human-gait images of different subjects of varying ages. The data sets have been formed in different covariant modes. The covariant modes mean capturing of human-gait images when the subject is walking with or without wearing shoes, and also the subject is walking with or without carrying loads and so on. Soft-computing techniques and forward-backward dynamic programming method have been applied for the best-fit selection of parameters and the complete matching process. The paretic and non-paretic characteristics have been classified through naïve baye's classification theory. The classification and recognition has been done in parallel with both test and trained data sets and the whole process of investigation has been successfully carried out through an algorithm developed in the present work. The success rate of behavioural trait detection is 89%.

Key words

Radon transforms, paretic characteristics, non-paretic characteristics, forward-backward dynamic programming, soft computing technique.

1. Introduction

Analysis of human walking movements, or gait, has been an ongoing area of research since the advent of the still camera in 1896. Since that time many researchers have investigated the dynamics of human-gait in order to fully understand and describe the complicated process of upright bipedal motion [1-4].

A number of areas have emerged in which considerable research has been done that exploits the analysis of this motion. These areas include clinical gait analysis, used for rehabilitation purposes, and biometric gait analysis for automatic person identification.

In the year 2002 Ben-Abdelkader et al. [5] proposed a parametric method to automatically identify people in low-resolution video by estimating the height and stride parameters of their gait. Later in the year 2004 Ben-Abdelkader et al. [4] has proposed a method that interprets the human gait as synchronized, integrated movements of hundreds of muscles and joints in the body. Kale and his colleagues [6] carried out work on appearance-based approach to the problem of gait recognition. In their work the width of outer contour of the binarized silhouette of a walking person is chosen as the basic image feature. Huang et al. [7] in the year 1998 proposed an approach to recognize people by their gait from a sequence of images. They have proposed a statistical approach which combined with eigen-space transformation with canonical space transformation for feature transformation of spatial templates. Cunado et al. [8] in the year 1997 proposed a method for evidence gathering technique. The proposed techniques have been developed for a moving model, representing human thighs, and to provide a gait signature automatically from the motion of the thighs. Phillips et al. [9] in the year 2002 proposed a baseline algorithm for the challenge problem of human identification using gait analysis. In the same year Phillips and his colleagues [10] worked on the baseline algorithm and with a large set of video sequences to investigate important dimensions of gait identification challenge problem, such as variations due to view point, footwear, and walking surface. Wang et al. [11] in the year 2008 have introduce Gaussian process dynamic models for non-linear time series analysis to learn models of human pose and motion from high dimensional motion capture data. The model proposed by Wang et.al [11] comprises a low-dimensional latent space with associated dynamics, as well as a map from the latent space to an observation space. Sina Samangooei and M. S. Nixon [12] in the year 2008 have proposed a set of semantic traits discernible by humans at a distance outlining their psychological validity. Imed Bouchrika et al. [13] in the year 2011 have investigated the translation of gait biometrics for forensic use. They have used the locations of ankle, knee and hip to derive a measure of match between walking subjects in image sequence. The match is achieved by instantaneous posture matching which determines the difference between the positions of a set of human vertices. Sinha et al. [14] in the year proposed a technique for detection of abnormal foot through human-gait images. So far, many researches have been done for the recognition of individuals, for finding the foot problems through human-gait images. But a little amount of work has been carried out, by investigating muscle activation and contraction for the detection of behavioural trait through human-gait images. Keeping this objective, in the present work, a methodology based on soft-computing technique has been proposed for the detection of behavioural trait during human walking through human-gait images.

The paper has been organized in the following manner -: section 2 proposes the solution methodology with mathematical formulations, section 3 describes the results and discussions, section 4 gives the concluding remarks and further scope of the work. Finally the last section incorporates all the references been made for the completion of this work.

2. Solution methodology with mathematical formulations

The investigation of muscle activations and contractions has been done through the implementation of soft-computing technique. The soft-computing technique involves artificial neural network, genetic algorithm and fuzzy set theory. Hence for the computation of muscle activation, the firing concepts of artificial neural network have been incorporated. As per the literature and through experimental setup of the present work, it has been found that, a neuron is fired when the output is more than its threshold value. Here in this present work, a sigmoid threshold function has been utilized for the computation of muscle activation. As a matter of fact, during the initial start of walking by any subject, the neuron fires and hence the muscle activates. Each neuron has an input and output characteristics and performs a computation or function of the form, given in equation (1):

$$O_i = f(S_i) \text{ and } S_i = W^T X \tag{1}$$

where $X = (x_1, x_2, x_3, \ldots, x_m)$ is the vector input to the neuron and W is the weight matrix with w_{ij} being the weight (connection strength) of the connection between the j^{th} element of the input vector and i^{th} neuron. W^T means the transpose of the weight matrix. The f (.) is an activation or nonlinear function (usually a sigmoid), O_i is the output of the i^{th} neuron and S_i is the weighted sum of the inputs.

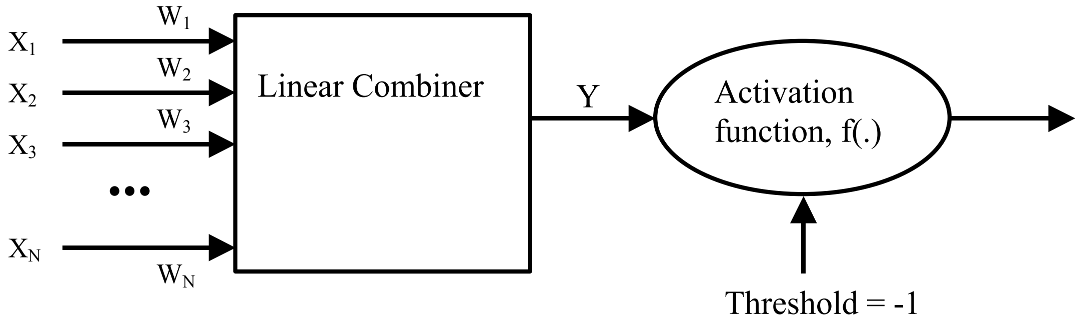

Fig.1. A simple artificial neuron

The real power comes when a single neuron is combined into a multi-layer structure called artificial neural networks. The neuron has a set of nodes that connect it to the inputs, output or other neurons called synapses. A linear combiner is a function that takes all inputs and produces a single value. Let the input sequence be $\{X_1,X_2,\ldots,X_N\}$ and the synaptic weight be $\{W_1,W_2,W_3,\ldots.,W_N\}$, so the output of the linear combiner, Y, yields to equation (2),

$$Y = \sum_{i=1}^{N} X_i W_i \tag{2}$$

An activation function will take any input from minus infinity to infinity and squeeze it into the range –1 to +1 or between 0 to 1 intervals. Usually an activation function being treated as a sigmoid function that relates as given in equation (3), below:

$$f(Y) = \frac{1}{1+e^{-Y}} \tag{3}$$

The threshold defines the internal activity of the neuron, which is fixed to –1. In general, for the neuron to fire or activate, the sum should be greater than the threshold value. This has been analyzed further by considering frame by frame data of the human walking.

The human-gait images have been fed as input for the computation of more additional parameters. The additional parameters are first the real-valued, second the neutral, third the normalized and finally the optimized and normalized parameter.

Mathematically, this has been discussed below:

Consider 'Z' numbers of frames have been read. Each frame has been read as $FRAME_1$, $FRAME_2$, $FRAME_3$, $FRAME_4$, ……$FRAME_{Z-2}$, $FRAME_{Z-1}$, $FRAME_Z$. The whole process has been taken care with the following facts:-

- Read the first frame from left to right direction
- Extract step-length parameter, P_{1L}
- Similarly read the first Frame from right to left direction

- Similarly extract step-length parameter, P_{1R}
- Compute average step-length parameter $F_{1avg} = (P_{1L} + P_{1R}) / 2$

Where P_{1L} signifies step length of first frame with left-to-right direction and

P_{1R} signifies step length of first frame with right-to-left direction and

F_{1avg} signifies average step length of first frame with both directions.

Repeat the above process for the next frames. Hence it yields to the average step-length measures as real-valued parameter like $F_{2avg} = (P_{2L} + P_{2R}) / 2$, $F_{3avg} = (P_{3L} + P_{3R}) / 2$, $F_{4avg} = (P_{4L} + P_{4R}) / 2$, $F_{5avg} = (P_{5L} + P_{5R}) / 2$,…………..…,$F_{(Z-1)avg} = (P_{(Z-1)L} + P_{(Z-1)R}) / 2$,

$$F_{Zavg} = (P_{ZL} + P_{ZR}) / 2 \tag{4}$$

Next to compute the neutral parameter, consider the 'even' and 'odd' frames separately. Let 'N_{odd}' and 'N_{even}' be the number of odd and even frames respectively. Hence, the neutral parameter yields to,

$$F_{Oddavg} = (F_{1avg} + F_{3avg} + \dots\dots\dots + F_{(2Z-1)avg}) / N_{odd} \tag{5}$$

$$F_{Evenavg} = (F_{2avg} + F_{4avg} + \dots\dots\dots + F_{(2Z)avg}) / N_{even} \tag{6}$$

The normalized parameters for each frame have been further computed. The solution yields for 'odd' frames,

$$F_{Norm1} = \frac{F_{1avg} - F_O}{F_{Oddav}}, \quad F_{Norm3} = \frac{F_{3avg} - F_O}{F_{Oddav}}, \quad F_{Norm5} = \frac{F_{5avg} - F_O}{F_{Oddav}},$$

$$\dots\dots \quad F_{Norm(2Z-1)} = \frac{F_{(2Z-1)avg} - F_O}{F_{Oddavg}} \tag{7}$$

Similarly for 'even' frames,

$$F_{Norm2} = \frac{F_{2avg} - F_{Evens}}{F_{Evenavg}}, \quad F_{Norm4} = \frac{F_{4avg} - F_{Evens}}{F_{Evenavg}}, \quad F_{Norm6} = \frac{F_{6avg} - F_{Evens}}{F_{Evenavg}}, \dots\dots$$

$$F_{Norm2Z} = \frac{F_{(2Z)avg} - F_{Evens}}{F_{Evenavg}} \tag{8}$$

Further computing the average neutral and normalized parameters (NNP) for 'odd' nd 'even' components, the solution yields to,

$$F_{NormOddavg} = (F_{Norm1} + F_{Norm3} + \dots + F_{Norm(2Z-1)}) / N_{odd} \tag{9}$$

$$F_{NormEvenavg} = (F_{Norm2} + F_{Norm4} + \dots\dots + F_{Norm(2Z)}) / N_{even} \tag{10}$$

Next is to compute the average neutral and normalized parameter (NNP) for each frame of the dataset, the solution yields to,

$$F_{NNP1} = \frac{F_{Norm1} - F_{NormO}}{F_{NormOddav}}, \quad F_{NNP3} = \frac{F_{Norm3} - F_{NormO}}{F_{NormOddav}}, \quad F_{NNP5} = \frac{F_{Norm5} - F_{NormO}}{F_{NormOddav}}, \quad \dots.$$

$$F_{NNP(2Z-1)} = \frac{F_{Norm(2Z-1)} - F_{NormO}}{F_{NormOddavg}} \tag{11}$$

Similarly for ‘even’ frames,

$$F_{NNP2} = \frac{F_{Norm2} - F_{NormEvens}}{F_{NormEvenavg}}, \quad F_{NNP4} = \frac{F_{Norm4} - F_{NormEvens}}{F_{NormEvenavg}}, \quad F_{NNP6} = \frac{F_{savg} - F_{Evens}}{F_{Evenavg}}, \ldots\ldots\ldots$$

$$F_{NNP(2Z)} = \frac{F_{Norm(2z)} - F_{NormEvens}}{F_{NormEvenavg}} \tag{12}$$

In general the dimensions of the feature vectors are of higher dimensions. In the present work, for better results during classification and recognition process the dimensions of these feature vectors have been reduced to lower dimensions, using forward-backward dynamic programming method. To illustrate this method mathematically, the following initial conditions have been set.

- Limit the area over which the search has to be performed
- Searching must be performed using constraints for the computation of best dynamic characteristics of human-gait

Assume two distinguished human-gait walking patterns, say $x(t_i)$ and $x(t_j)$ are defined, each with its own time base, t_i and t_j. Also assume that the beginning and end of the walking pattern are known, denoted as (t_{is}, t_{if}) and (t_{js}, t_{jf}) respectively. If both the patterns are sampled at the same rate, then both patterns begin ‘t’ sample i = j = 1, that occurs without any loss of generality. Thus, the mapping function, i = j . (I / J), is linearly related. As the human-gait patterns appear non-linear, so non-linear time warping functions are calculated, with several assumptions. Let the warping function, w(k), be defined as a sequence of points: c(1), c(2), …..,c(k), where c(k) = (I(k), j(k)) is the matching of the point i(k) on the first time-base and the point j(k) on the second time-base. This has been summarized in figure 2, below,

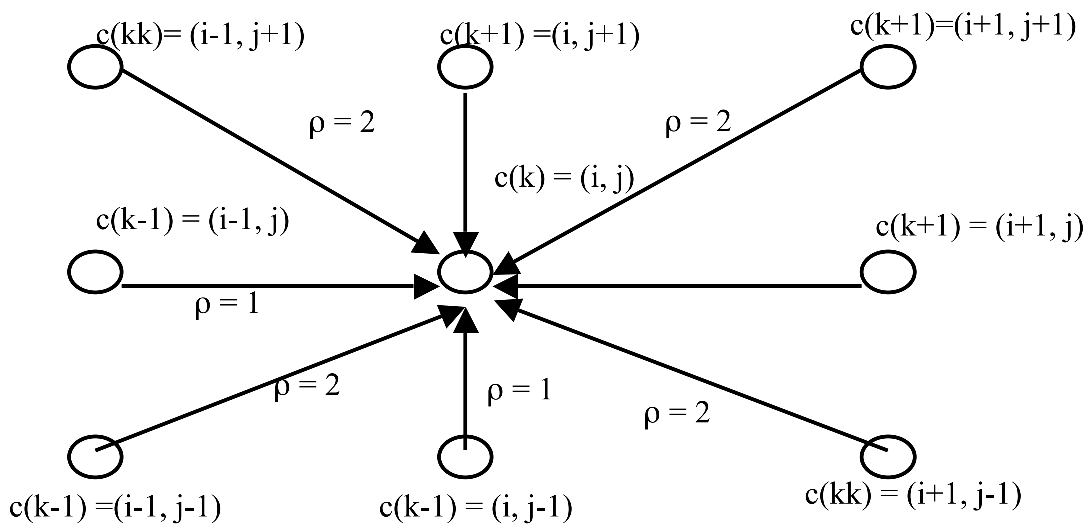

Fig.2. Searching constraints for the computation of best dynamic characteristics of human-gait

From figure 2, it has been analyzed that the chances of walking by the human-gait are distinguished into five directions.

- Horizontally left to right movement and horizontally right to left movement (parallel to x-axis)
- Diagonally left to right and diagonally right to left (45 degree to x-axis)
- Diagonally right to left and diagonally left to right (135 degree to x-axis)
- Vertically (parallel to y-axis)
- Circularly clock-wise direction and circularly anti-clock-wise direction

Setting the initial conditions let the search window be restricted to the limit:

$\left|i - j.(I/J)\right| \leq \gamma$, where γ is some constant.

From figure 2, the warping, w(k), only allows to compare the appropriate parts of $x(t_i)$ with that of $x(t_j)$. Setting the monotonic and continuity conditions on the warping function, it restricts to the relations between four consecutive warping points, c(k), c(k-1) c(k+1) and c(kk), where kk signifies +/- or -/+.

Thus from figure 2, there are eight ways to get to the point c(i,j), which has been given in equations (13), (14), (15) and (16), below,

$$c(k) = c(i,j) \tag{13}$$

$$c(k-1) = \begin{cases} (i(k), j(k)-1) \\ (i(k)-1, j(k)-1) \\ (i(k)-1, j(k) \end{cases} \tag{14}$$

$$c(k+1) = \begin{cases} (i(k), j(k)+1) \\ (i(k)+1, j(k)+1) \\ (i(k)+1, j(k) \end{cases} \tag{15}$$

$$c(kk) = \begin{cases} (i(k)-1, j(k)+1) \\ (i(k)+1, j(k)-1) \end{cases} \tag{16}$$

And the boundary condition or circular movements yields to,

$$c(k) = (I,J) \tag{17}$$

By the boundary condition, matching of the beginning and end of the walking pattern and the tracing the optimal route for normal walking has been done using forward-backward dynamic programming method. To formulize this method for the tracing of the best matching, the walking patterns have been represented at each point, by their feature vectors, $\beta_i(k)$ and $\beta_j(k)$, where $\beta_i(k)$ denotes the feature vector of the walking pattern $x(t_i)$ and $\beta_j(k)$ denotes the feature vector of the walking pattern $x(t_j)$. On defining a distance measure between the two feature vector by,

$$d(c(k)) = d(i(k),j(k)) = \left|\beta_i(k) \quad - \quad \beta_j(k)\right| \tag{18}$$

Next searching for the warping function, so that the performance index $D(x(t_i),x(t_j))$ gets minimized. The performance index is the normalized average weighted distance, which has been related as,

$$D(x(t_i),x(t_j)) = \underset{w}{Min}\left[\frac{\sum_{k=1}^{k} d(c(k))\rho(k)}{\sum_{k=1}^{k}\rho(k)}\right] \tag{19}$$

where $\rho(k)$ are the weights, that yields to I + J, Thus equation (17) results to,

$$D(x(t_i),x(t_j)) = \frac{1}{I+J}\underset{w}{Min}\left[\sum_{k=1}^{k} d(c(k))\rho(k)\right] \tag{20}$$

On substituting the values of equations (13), (14), (15) and (16) in equation (20), each point in the search window has been attached with information for an optimal match upto its destination point (I, J). This way of searching is said to be forward technique of dynamic programming. After scanning has terminated, construction of an optimal match has been carried out by going backward from (I,J) to (0,0) or (1,1) point. This way of searching is said to be backward technique of dynamic programming and the reversal process is said to be forward technique of dynamic programming. The combination of this two way of searching technique results to forward-backward dynamic programming searching method. For an optimal solution, minimum number of divergence values has been must be resulted, on searching. Thus to compute the divergence values for an optimal solution, let the probability of getting a feature vector, β, given that it belongs to some class w_i, yields, $p(\beta/w_i)$, similarly for the class w_j, yields $p(\beta/w_j)$. The sum of the average logarithmic ratio between these two conditional probabilities yields, information concerning the separability, between the two classes and found that there results no loss to the concept. This gives the divergence values of the features. Thus the mathematical formulation yields,

$$D_{i,j} = (\mu_i - \mu_j)\,(\mu_i - \mu_j)^T\Sigma^{-1} \tag{21}$$

where $\mu = \mu_i = \mu_j$ means the expectations and Σ mean the covariance.

From equation (21) divergence values have been calculated upto 19 feature vectors.

2.1 Mathematical analysis for behavioural trait detection

The mathematical analysis for the detection of behavioural trait through human-gait image has been formulated using two features: step-length and walking-speed.

Let the source be ‘S’ and the destination be ‘D’. Also assume that normally this distance is to achieve in ‘T’ steps. So ‘T’ frames or samples of images are required. Considering the first frame, with left-foot (F_L) at the back and right-foot (F_R) at the front, the coordinates with (x,y) for first frame, such that $F_L(x_1,y_1)$ and $F_R(x_2,y_2)$. Thus applying Manhattan distance measures, the step-length has been computed and it yields to,

$$|step-length| = |x_2 - x_1| + |y_2 - y_1| \tag{22}$$

Let normally, T_{act} steps are required to achieve the destination. From equation (22), T_1 has to be calculated for the first frame. Similarly, for ‘nth’ frame, T_n has to be calculated. Thus total steps, calculated are,

$$T_{calc} = T_1 + T_2 + T_3 + \ldots\ldots + T_n \tag{23}$$

Thus walking-speed or walking-rate has been calculated and it yields to,

$$walking-speed = \begin{cases} norm & ,if \quad T_{act} = T_{calc} \\ fast & ,if \quad T_{act} < T_{calc} \\ slow & ,if \quad T_{act} > T_{calc} \end{cases} \tag{24}$$

Considering two measures, accuracy and precision has been derived to access the performance of the overall system, which has been formulated as,

$$\text{accuracy} = \frac{Correctly\ \mathrm{Re}cognized\quad feature}{Total\ number\ of\ \ features} \tag{25}$$

$$\text{precision} = \frac{TPD}{TPD + FPD} \tag{26}$$

where TPD = true positive detection and FPD = false positive detection.

Further analysis has been done for the classification of behavioural traits with two target classes (normal and abnormal). It has been further illustrated that the corpus developed in the present work has various states, each of which corresponds to a segmental feature vector. In one state, the segmental feature vector is characterized by nineteen parameters. Considering only three parameters: the step_length: distance, mean, and standard deviation, the model yields to an equation given in equation (27).

$$\text{AHGM}_1 = \{D_{s1}, \mu_{s1}, \sigma_{s1}\} \tag{27}$$

where AHGM_1 means an artificial human-gait model of the first feature vector, D_{s1} means the distance, μ_{s1} means the mean and σ_{s1} means the standard deviation based on step_length. Let

w_{norm} and w_{abnorm} be the two target classes representing 'normal behaviour' and 'abnormal behaviour' respectively. The clusters of features have been estimated by taking the probability distribution of these features. This has been achieved by employing Bayes decision theory. Let $P(w_i)$ be the probabilities of the classes, such that, i = 1,2,….M also let $p(\beta/w_i)$ be the conditional probability density. Assume a test human-gait image represented by the features, β. So, the conditional probability $p(w_j/\beta)$, which belongs to j^{th} class, is given by Bayes rule as,

$$P(w_j/\beta) = \frac{p(\beta/w_j)P(w_j)}{p(\beta)} \tag{28}$$

So, for the class j = 1 to 2, the probability density function p(β), yields,

$$P(\beta) = \sum_{j=1}^{2} p(\beta/w_j)P(w_j) \tag{29}$$

Equation (28) gives a posteriori probability in terms of a priori probability $P(w_j)$. Hence it is quite logical to classify the signal, β, as follows,

If $P(w_{norm}/\beta) > P(w_{abnorm}/\beta)$, then the decision yields $\beta \in w_{norm}$ means 'normal behaviour' else the decision yields $\beta \in w_{abnorm}$ means 'abnormal behaviour'. If $P(w_{norm}/\beta) = P(w_{abnorm}/\beta)$, then it remains undecided or there may be 50% chance of being right decision making. During this situation further analysis has been done through fuzzy c-means clustering technique.

2.2 Proposed algorithm

The proposed algorithm for the detection of behavioural trait with proper investigation of muscle activation and contraction has been given below.

1. Read the original image, convert the RGB image into gray scale image
2. Perform filtering for the removal of noise from the gray scale image
3. Employ morphological components for obtaing the thinning and thickening image
4. Crop the image after extraction of features and relevant parameters
5. Employ radon transform, normalization technique for computing muscle activation
6. Set the angle value for the parallel projection of data, say theta1, theta2, theta3 and theta4
7. Set four counter values for parallel projections as 12, 18 , 36 and 90.
8. Employ inverse radon transform method for the regeneration of cropped image with parallel projections.
9. Select the best fit parameters for the matching using forward-backward dynamic programming method

10. Validate the above process using genetic algorithm
11. Employ classification process using baye's theory. If the classification value is 50% then employ fuzzy c-means clustering technique and check for gaid-code using UTAM technique.
12. Employ decision making process and finally plot the results

3. Results and discussions

In the present work, first a human-gait image has been captured through eight digital cameras placed at a known fixed distance and fed as input for the investigation. Next it has been enhanced and hence loss-less compression technique called discrete cosine transform has been applied for the removal of distortions. Further it has been segmented for contour detection and the relevant physiological features have been extracted. All the features of the human-gait image are stored in a corpus called automatic human-gait model. In figure 3, the segmented output of the original human-gait image has been shown in walking mode. Relevant biometrical features with covariant mode (wearing no footwear) have been extracted in the initial investigation of the present work. The relevant physiological feature, that is, step-length and knee-to-ankle distance has been also extracted that has been shown in figure 4, figure 5 and figure 6. The values of these extracted features have been shown in table 1.

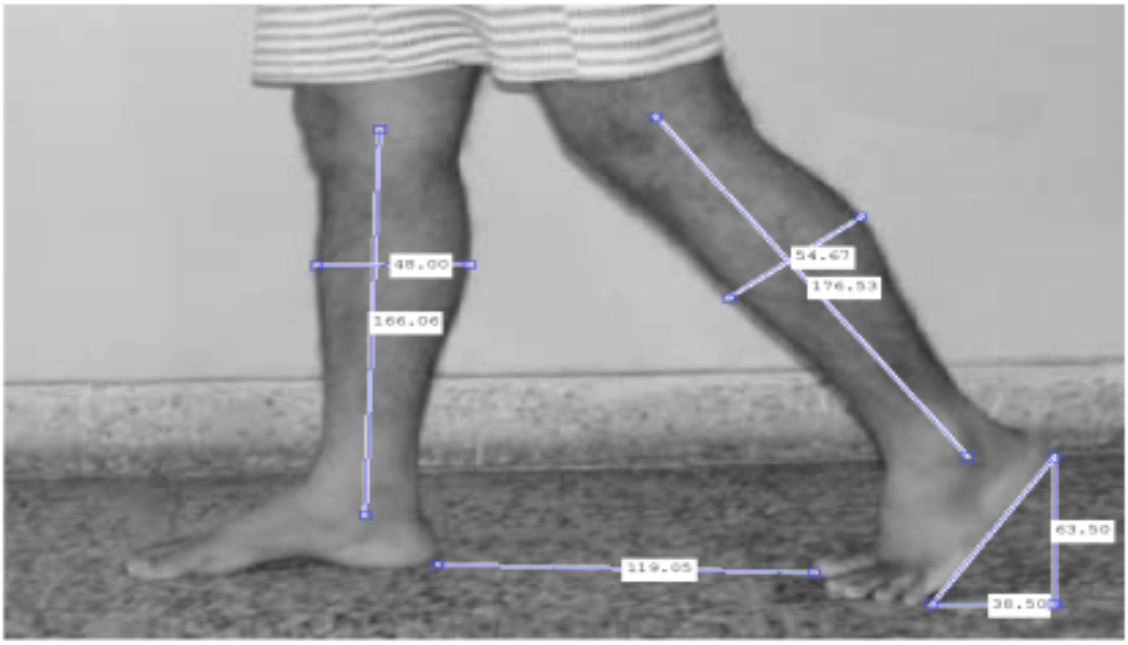

Fig.3. Covariant mode of human-gait in walking mode of subject with right leg at the front

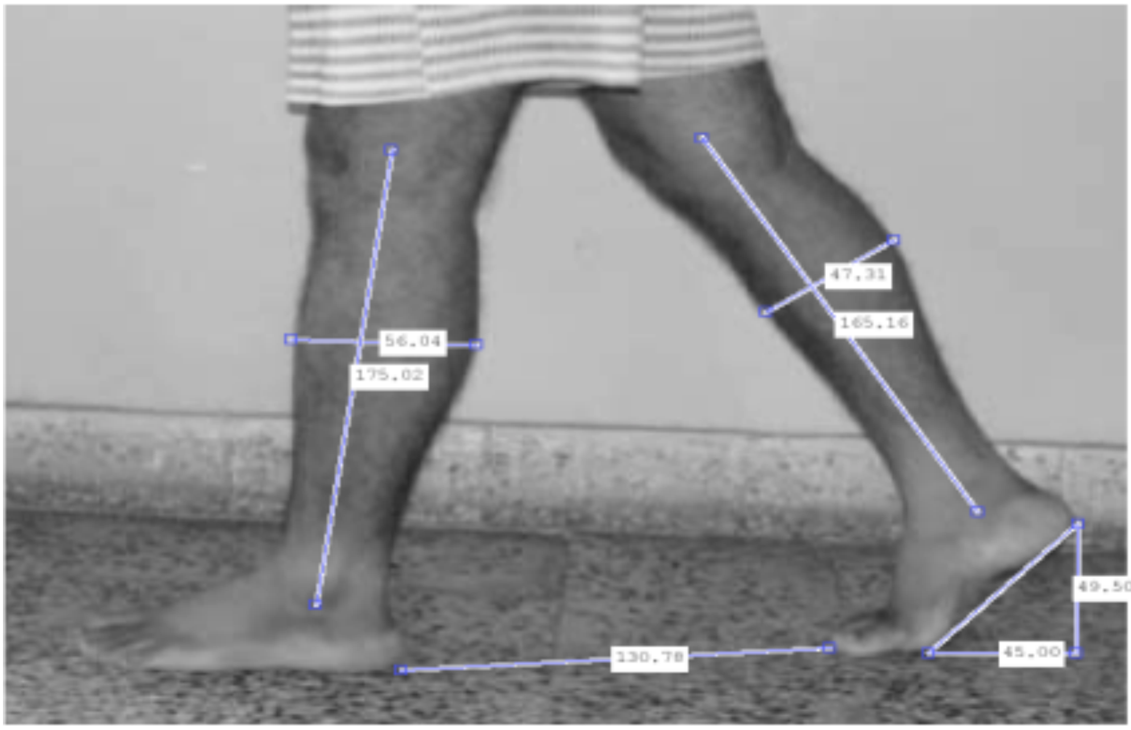

Fig.4. Covariant mode of human-gait in walking mode of subject with left leg at the front

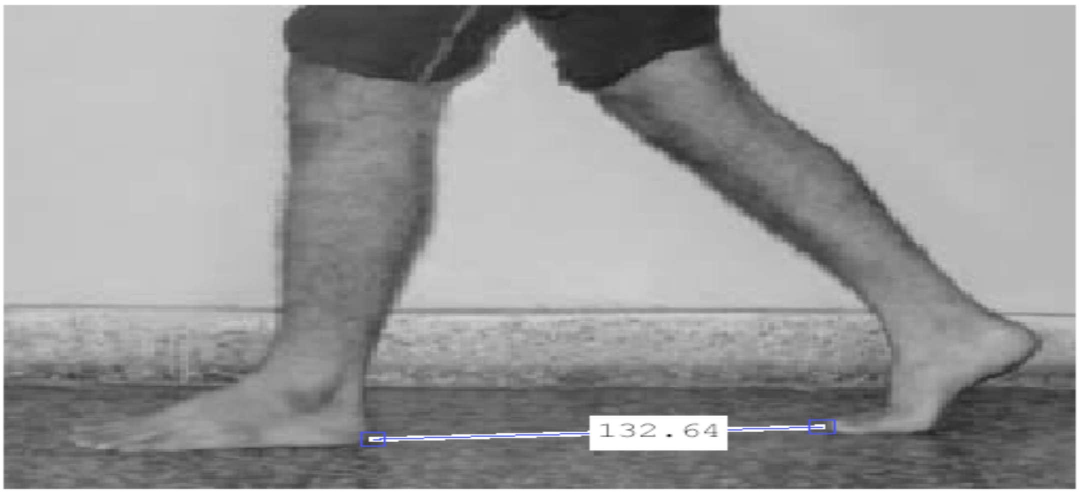

Fig.5. Step-length measure with covariant mode in walking mode of the subject

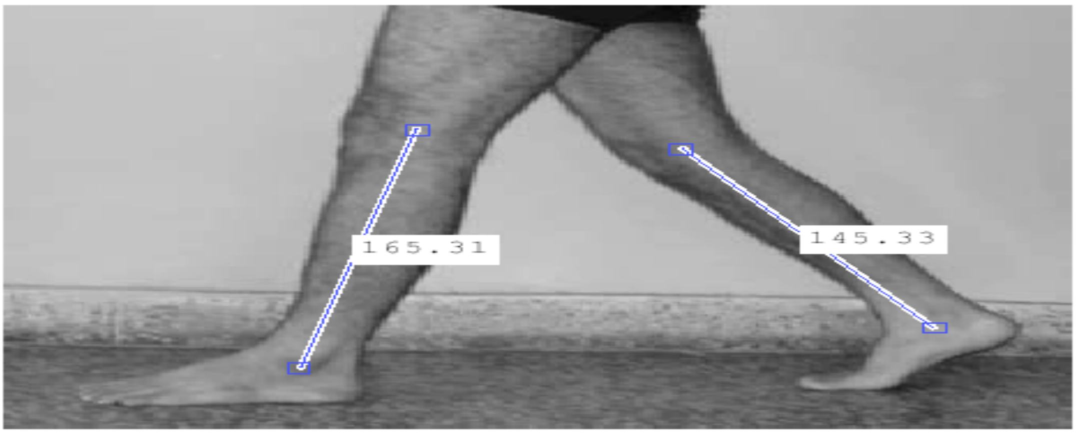

Fig.6. Knee-to-ankle measure with covariant mode in walking mode of the subject

Table 1. Features extracted for the detection of behavioral trait from human-gait image

Data Source	**Human-gait or physical characteristics**	**Foot angle in degrees**	**Step length in pixels**	**K_A distance in pixels (left leg)**	**K_A distance in pixels (right leg)**	**Foot length in pixels**	**Shank width in pixels (left leg)**	**Shank width in pixels (right leg)**
Img1	Standing (left leg facing towards camera)	0	0	176.0	176.5	103	54.6	54.5
Img2	Standing (right leg facing towards camera)	0	0	176.0	176.5	104	54.0	54.5
Img3	Walking (left leg movement)	60.6	122.5	175.8	165.5	102	54.3	47.5
Img4	Walking (right leg movement)	47.0	129.4	176.1	165.7	103	56.0	47.8
Img5	Walking (left leg movement)	58.7	119.0	176.5	166.0	101	54.6	48.0
Img6	Walking (right leg movement)	47.7	130.7	175.6	165.1	104	56.0	47.3

From table 1, it has been observed that minimum variations have been found from one frame to other. This has been plotted in figure 7, below, for the graphical analysis.

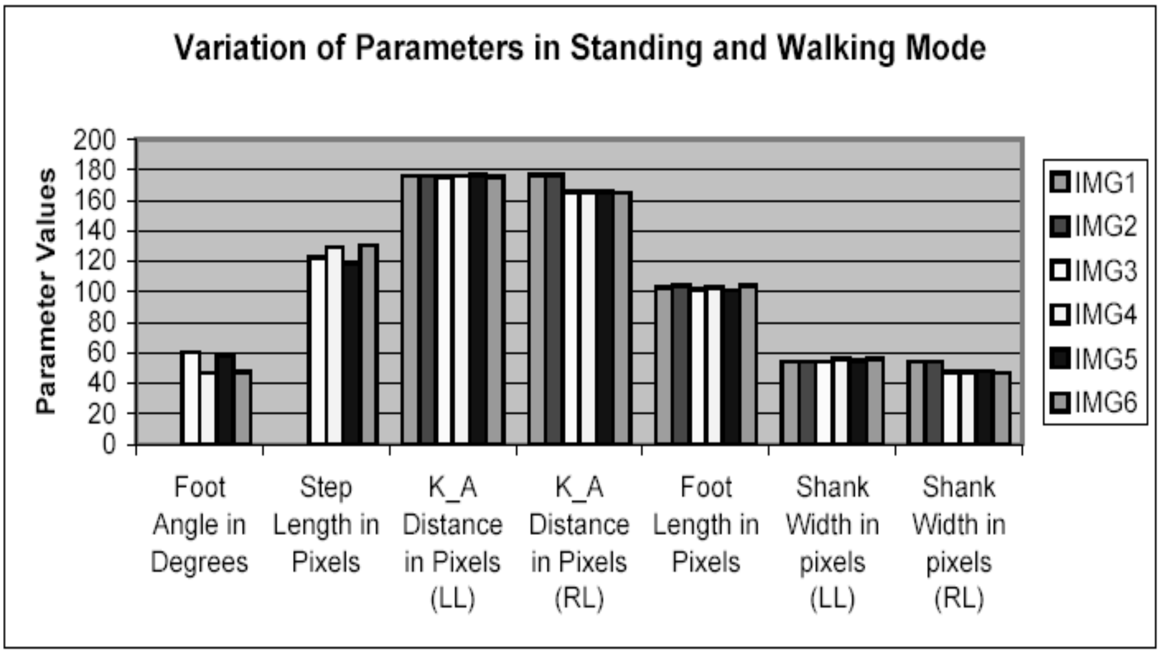

Fig.7. Graphical representation of features extracted during standing and walking mode

After the extraction of relevant features, limited number of parameters have been utilized for the computation of muscle activation and contractions. For this radon transform method and its inverse mechanism has been applied and the relevant output of the algorithm has been obtained which are shown in figure 8, figure 9 and figure 10.

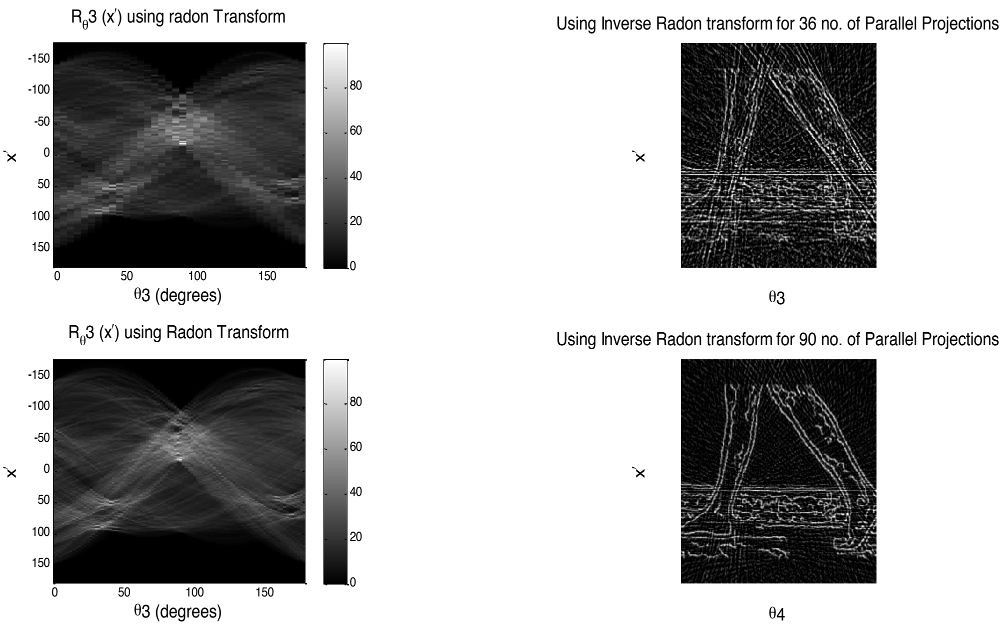

Fig.8. Muscle activation and contraction with projection count 36 and 90

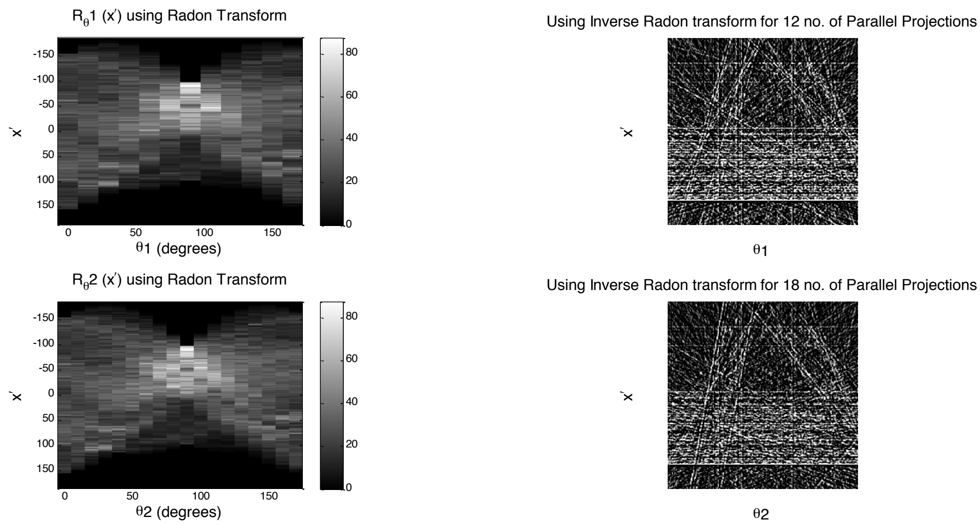

Fig.9. Muscle activation and contraction with projection count 12 and 18

From figure 8 and figure 9, it has been observed that the projection at 90 degree is having wider profile than at 0 degree projection. This means the enery and intensity value of muscle activation and contraction appears maximum when the angle for parallel projection of extracted data is at 90 degree. The behavioural pattern matching of test data sets stored in a corpus called automatic human-gait model (AHGM) for one subject has been shown in figure 10.

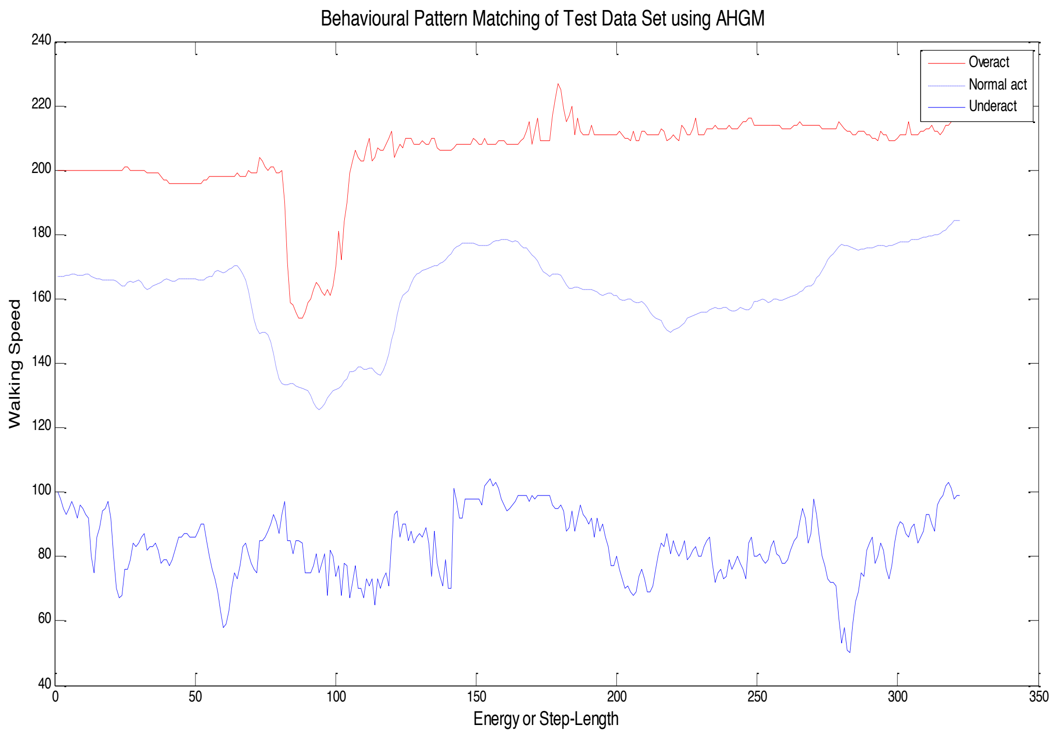

Fig.10. Behaviour pattern matching of test data set using AHGM of a subject gait (ten seconds walk) with overact, normal act and underact moods.

From figure 10, it can be observed that three traits or moods of behaviour have been analysed: over act, normal act and under act. The behaviour is normal, when there is no presence of perturbations in the behavioural characteristic curve. When large number of perturbations is available in the behavioural characteristic curve, then it is under act behaviour. When smaller number of perturbations is available in the behavioural characteristic curve; then it is under over act behaviour [15]. This has been further illustrated for both trained data sets and test data sets, considering one subject which is shown in figure 11.

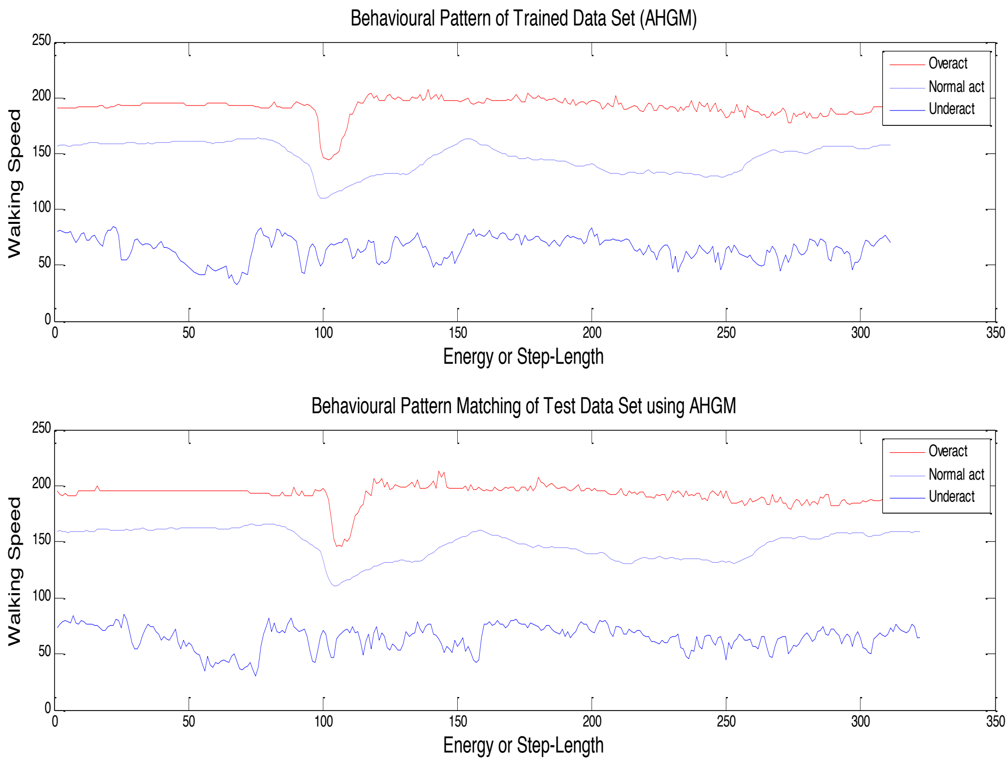

Fig. 11.Behavioural pattern matching of the same subject gait (one second walk) with overact, normal act and underact moods.

This has been also illustrated for both trained and test data sets, considering two different subjects which is shown in figure 12.

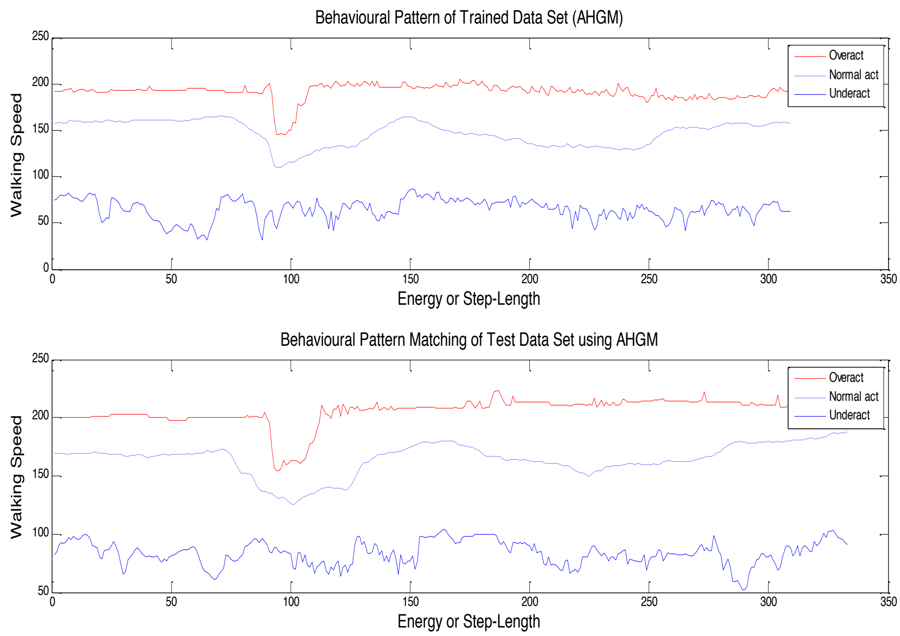

Fig.12. Behavioural pattern matching of two different subjects gait (one second walk) with overact, normal act and underact moods.

This has been also illustrated for both trained and tests data sets, considering both the frames of walking cycle, that is odd and even cycle, which is shown in figure 13.

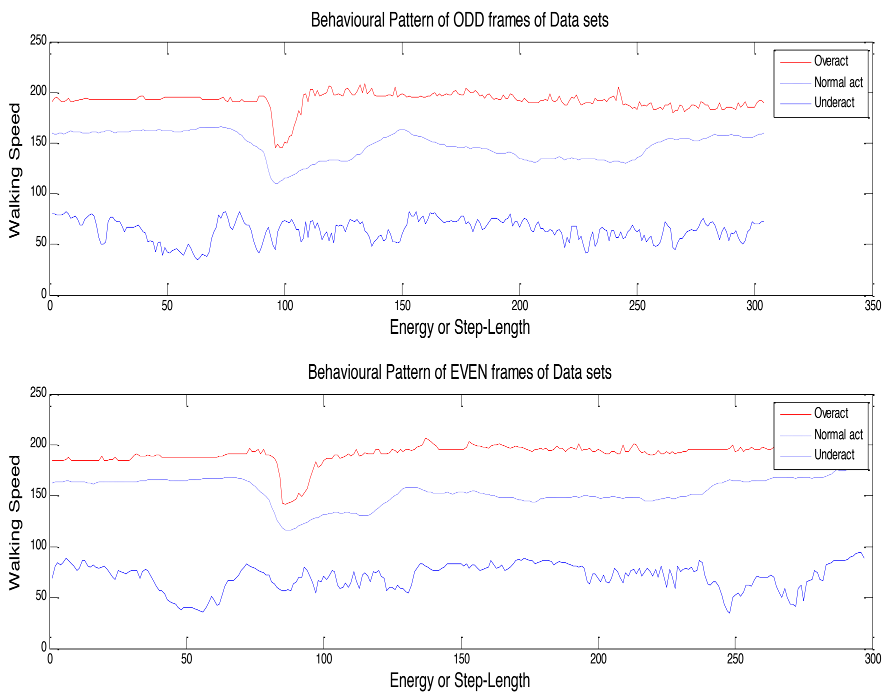

Fig. 13. Behavioural pattern of odd and even frames of the same female subject gait (ten seconds walk) with overact, normal act and underact moods.

The clusters of features for the detection of behavioural pattern or trait of a human-gait have been plotted using fuzzy c-means clustering method, and the result is shown in figure 14.

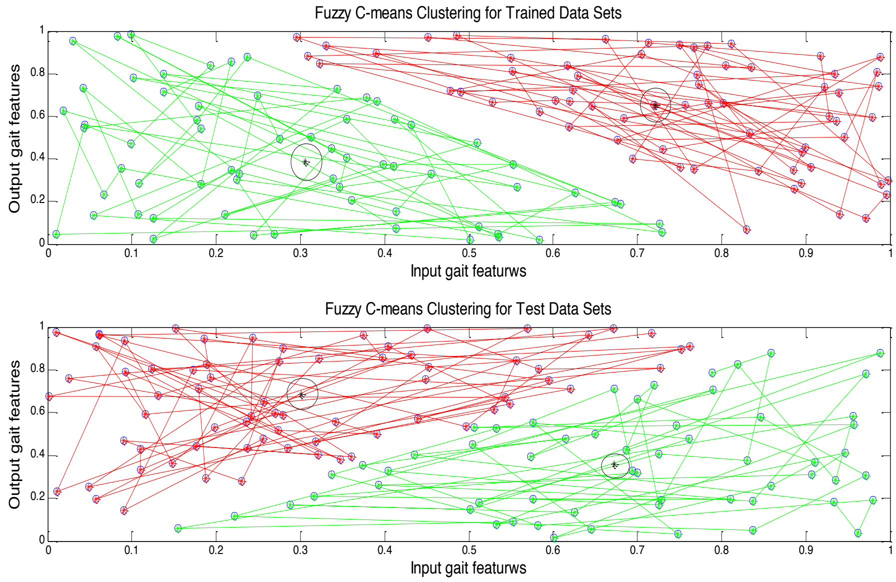

Fig. 14. Clusters of features for the detection of behavioural pattern using fuzzy c-means algorithm of a subject gait (ten seconds walk).

A boundary has been formed, as shown in figure 15, for the detection of gait-code using unidirectional temporary associative memory (UTAM) technique of artificial neural network.

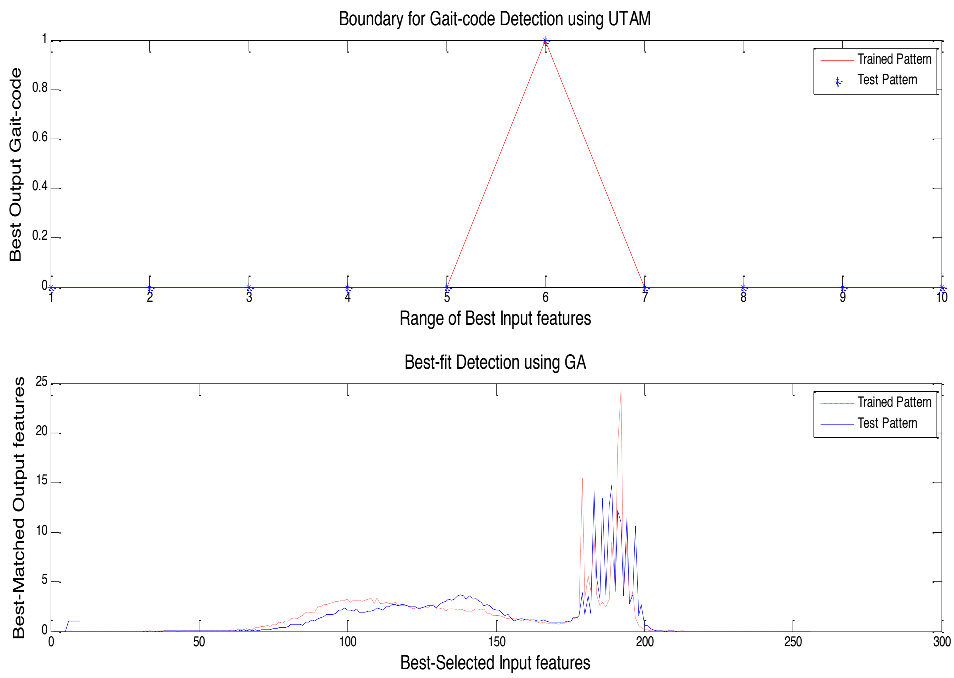

Fig. 15. Boundary for gaitcode detection using uni-directional temporary associative memory (UTAM) and best-fit detection using genetic algorithm of a subject gait (ten seconds walk).

The overall behavioural pattern for trained and test data sets has been shown in figure 16.

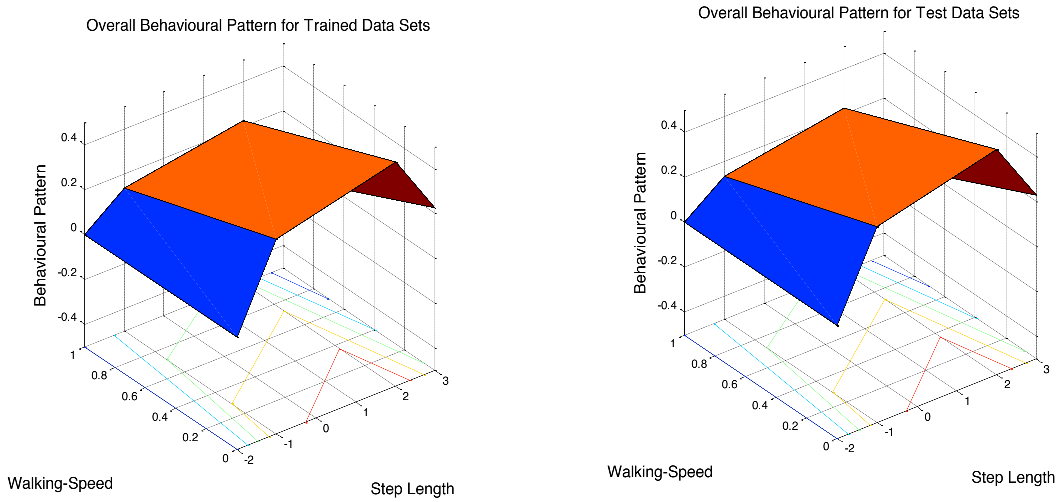

Fig. 16. Overall behavioural pattern of a subject gait (ten seconds walk) for both trained and test data sets.

4. Conclusions and further scope of the work

The results obtained so far have to be further analyzed using fan-beam projection method for more accurate values of muscle activation and contraction. Further the volume of the corpus has to be increased and further analysis has to be done with the developed algorithm and also statistical and high-end computing measures have to be carried out using known algorithms from the literature. The analysis will be also based on performance measures with an optimal number of parameters for the recognition of the biometrical traits.

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