Evolutionary Computing Assisted Neural Network for Crowd Behaviour Classification

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Abstract:

The dramatic ascent in advancements and associated applications have generally revived the scholarly community enterprises to accomplish more effective and strong answer to satisfy contemporary needs. Reconnaissance frameworks have drawn in mainstream researchers to empower occasions to settle on convenient choice interaction. This paper proposes a robust model to perform multi-class classification using Evolutionary Computing algorithm named Binary Bat Algorithm based Multi-Feed Forward Neural Network model (BBA-MFNN). Here, the utilisation of GLCM and AlexNet features provides deep spatio-temporal feature information helps to make optimal classification decision and the proposed BBA-MFNN algorithm enables optimal multi-class classification while avoiding local minima and convergence problem which can often be present in video data analysis due to non-linear feature distribution. Thus, the proposed model accomplishes Crowd Behaviour analysis with an accuracy of 96.15%, precision of 94.66%, 96.52% recall and F-Measure of 95.56%, which is higher than the classical MFNN classifier.

Keywords – *Crowd Behaviour Analysis, Hybrid Deep Features, GLCM, AlexNet, Binary Bat Algorithm, Feed Forward Neural Network*

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I. Introduction

An increase in the number of deployed video-surveillance tools require real-time analytical provision which can be fulfilled by means of highly robust intelligent systems possessing video-mining and feature learning ability. Crowd behaviour analysis has become a dominant research area [2]. Significance for analysing crowd behaviour has become paramount because of the increased demands of surveillance of various types of public gathering.

Crowd behaviour analysis deals with different issues such as crowd-size, behavioural change, transient movement changes, or anomaly detection [3-9] and crowd event recognition [10-14]. To accomplish crowd anomaly detection is essential in crowd videos. Crowd behaviour analysis methods can be classified as target-based approaches and holistic models [15]. In target or object-based approaches, crowd is the assortment of individuals in which first each individual must be segmented to characterize ones movement. In holistic model, the crowd is a global entity that helps to perform crowd analysis. Holistic models assess the dynamics of the complete scene rather than analysing particular actions of each individual. Optical flow histogram [7][61] represents the global motion in the video frame. The histogram obtained from optical flow analysis can be used to detect malicious crowd situation. A Probabilistic crowd event detection model was developed in [16], where based on individual's movement pattern such as running, walking, etc, crowd types were classified. Optical flow is used to perform crowd classification [16]. Temporal window based salient point tracking [8][10][17] and particle advection method have been applied for crowd analysis. Crowd motion representation and tracklets were used [8] to perform crowd analysis. Motion detection models [8] have also been used for crowd analysis. However, these approaches have numerous drawbacks, especially due to the characterization of the individual properties rather considering cumulative features, which could yield better performance. In addition, the use of interactions among the individuals can also be significant for crowd behaviour analysis [4][17][18][19-21]. A social force model was developed in [4][60] where the pedestrian movements' local characteristics were used to detect anomaly. In [18], chaotic invariants like maximal Lyapunov exponent and correlation dimensions were applied to perform abnormal crowd detection. Interaction action energy was also applied in [19] to signify the current state of an object along with its position and velocity to perform crowd analysis. Structural context descriptor was applied in [20] where authors exploited associations between each target for crowd analytics. Static as well as dynamic agents were applied in [21] to model personalized and group behavior of the crowd. Local motion patterns such as direction and velocity were used in [17] to perform crowd analysis. Recently, authors [22] recommended using mid-level features to classify crowd behavior. Template based approaches [23] too have been proposed for human action recognition, while statistical features have been found fair to make motion estimation and allied event classification [24].

Deep features helps perform target detection, tracking and classification purposes. Understanding the importance of statistical features of GLCM and deep features from CNN as combined feature vector [1], a highly robust and effective crowd behaviour analysis model is proposed. Our proposed model utilizes hybrid features [1] for crowd classification. Unlike conventional classifier, an evolutionary computing based classifier named Binary Bat Algorithm based Multi-Feed Forward Neural Network (BBA-MFNN) is intended to perform multi-class classification.

II. PROPOSED SYSTEM

Fig. 1 depicts the proposed method. It involves Data acquisition, Data Pre-processing, Hybrid deep feature extraction [1] and Classification using evolutionary BBA-MFNN algorithm.

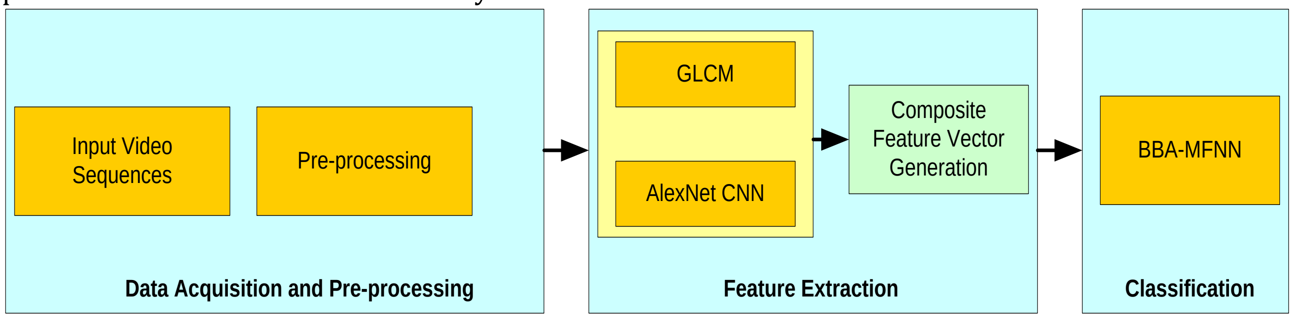

Fig. 1 Proposed crowd analysis and classification model

A. *Evolutionary computing Assisted NN based Multi-Class Classification*

Using hybrid features of [1] we projected it to an Evolutionary computing assisted Neural Network classifier model. More specifically, a robust Binary Bat Algorithm (BBA) based Multi-Feed Forward Neural Network (MFNN) is developed to conduct multi-class classification of different crowd videos. The detailed discussion of the developed classification model is given in the sub-sequent sections.

Considering at hand problem of analysis of crowd behaviour in videos, with enormous hidden neurons and large data sets, it could endure seriously causing premature convergence and false alarm. Improper edge-weight estimation in learning phase is the transcendent justification behind local minima and convergence. Considering this fact, we developed an Evolutionary Computing (EC) based MFNN model where EC intends to estimate the optimal or sub-optimal weight parameters to perform learning. Thus, obtaining the optimal set of weight parameters the learning has been performed to enable multi-class classification. Though, a number of EC algorithms or the heuristic models viz, Genetic Algorithm (GA), Flower Pollination Algorithm (FPA), Ant Colony System (ACS), Particle Swarm Optimization (PSO), Artificial Immune System (AIS), Cuckoo Search (CS), etc have been developed; however the efficacy of these algorithms often stay bound because of convergence issues, higher computation time and cost. Undeniably, GA has been found a better or potential EC solution to solve convex problems, its parameter (i.e., crossover and mutation probability) estimation and update has always been the challenge. Considering this fact, unlike classical EC algorithms, we have developed a novel EC model named Modified Binary Bat Algorithm (MBBA). Here, MBBA intends to optimize the weight(s) parameter of the MFNN and thus completes learning to deliver optimal crowd video classification by allied features learning and classification. The BBA-MFNN model is explained in detail in the sub-sequent sections.

BAT Heuristic Algorithm

Considering evolutionary aspects, after Odontocetes, Bats are the mammals possessing a highly strong sound propagation ability called Bio-SONAR, which is also known as echolocation. This ability helps Bat to identify obstacles in their path (when traversing) and prey. Typically, echolocation can present where the animals employ their sound for ranging purposes. In this phenomenon, the delay incurred in between the sound emission from the animal and the echoes received after striking the obstacles enables estimation of the actual target location and its range. On the other hand, Bats being a clever mammal adjust their movement pattern, velocity and the direction on the basis of the prey's presence and availability. Such peculiarity motivates researchers to exploit and employ this nature to design convex solutions in the form of Digital Bats Concept [67]. The ability of Binary Bat Algorithm (BBA) also called Digital Bat Concept (DBC) has been applied in numerous optimization problems [16][67]. Based on computational environment, different variants such as BBA [16], Multi Objective Bat Algorithm (MOBA) [68] Fuzzy Logic Bat Algorithm (FLBA) [13] etc have been proposed, though the working principle of these variants remains the same. Functionally, employing echolocation the Bat updates its velocity, direction, position and frequency to reach its prey swiftly. BBA exploits this feature to estimate the optimal set of weights to perform learning while reaching the target value or threshold. BBA model is initiated with a defined set of population (n) and frequency(F_{min}), initial loudness(A_0), pulse emission rate (r) and wavelength(λ). In addition, it is characterised by a velocityV_i, position vector $X_i$and a frequency vectorF_i, which are updated as per the need.

Before discussing BBA model, some of the key assumptions considered are given as follows.

- *The pulse-rate r is inversely proportional to the distance of the Bat from its prey. In other words, the value of r increases as Bat approaches to its prey.*
- *The loudness or intensity A is proportional to the distance of the Bat from its prey. In other words, with decrease in the distance between Bat and targets the loudness also reduces.*
- *The loudness A is hypothesized to be decreasing from A_0 to the minimal loudnessA_{min}.*
- *The inception frequency F_0 is allotted to the individual Bat arbitrarily existing in between$[F_{min}F_{max}]$.*

Here, the frequency parameters (limits) $F_{min}$and F_{max} are fixed on the basis of the problem size. Moreover, the Bat velocity and its vector are updated using

$$V_i(t+1) = V_i(t) + (X_i(t) - G_{Best})F_i \quad (1)$$

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

$$F_i = F_{min} + (F_{max} - F_{min})\beta$$

In (1), i signifies the non-negative integer in the range of 1 to $n$signifying the $i-th$ Bat. The variable t signifies the iteration, while G_{Best} refers the best solution retrieved. Here, the parameter $\beta$is arbitrarily generated in the range of$[0,1]$. Considering above equation (1-2), it can be observed that the disparity in frequency causes Bats to intend over retrieving the best solution to reach its prey. In this case, the optimal solution is obtained using

$$X_{new} = X_{old} + \varepsilon A^t \quad (2)$$

In (2), A^t signifies the mean of the intensity or the loudness of all participating candidate or Bats at certain iteration$t$. Here. εrefers a random number in the range of $[-1,1]$. Now to estimate the best solution, the Bat algorithm applies loudness and the updated values of the pulse rate r to explore the search space as per (3-4).

$$r_i(t+1) = r_i(0) + [1 - exp(-\lambda t)] \quad (3)$$

$$A_i(t+1) = \alpha A_i(t) \quad (4)$$

In (22-23), the parameter λ and α are the constant values, while $r_i(0)$ states the final value of the pulse rate r_i. Noticeably, once $r_i$approaches $r_i(0)$, A_i becomes zero signifying that the Bat has reached to it prey or the target. This approach is applied to perform iterative parameter update till reaching the final solution. Unlike classical Bat Algorithm, in this paper we have applied an improved BBA algorithm to update MFNN weights for better learning and classification.

A. Binary Bat Algorithm (BBA)

Typically, BBA follows the similar functional approach as is applied by Bat algorithm, however it differs in terms of search space dimensions. In other words, the classical Bat algorithm exhibits in continuous search space, while BB functions in binary search space (BSS). The BSS being constrained to "0" and "1", the probability of velocity and Bat's position can be obtained using (1-4). However, it is must to have a robust approach to use velocity information dynamically for changing and updating the movement pattern or velocity and position. Thus, to update the position information of BBA, it is must to map the velocity information to the likelihood values. It can be achieved by applying certain transfer function. This specific transfer function is required to be constrained or bounded in the interval of [0 1] and the results (of the transfer function) must be proportional to the change in velocity. Considering this fact, we applied a function named Hyperbolic Tangent Function (HTF) as per (5). This function enabled mapping of the parameters from continuous domain to the binary domain.

$$V\left(v_i^k(t)\right) = tanh\left(v_i^k(t)\right) \tag{5}$$

Thus, employing tanh transfer function, we performed the likelihood based positional variations or changes of an agent, also called Binary Bat. Mathematically, the position change and/or update is performed using

$$if\left(rand < V\left(v_i^k(t+1)\right)\right) \tag{6}$$

$$X_i^k(t+1) = X_i^k(t)'$$

else $X_i^k(t)$

In (6), the parameter $v_i^k(t)$ and $X_i^k(t)$ signifies the velocity and position values of the i^{th} Binary Bat in k^{th} dimension at t^{th} iteration. Similarly, the compliment of the parameter $X_i^k(t)$is given as $X_i^k(t)'$. A snippet of the BBA algorithm developed is given below.

Algorithm 1: Pseudo algorithm for BBA heuristic

1. Initialise Population $X_i(i = 1,2, \dots, n)$, random variable (0, 1) and velocity $V_i = 0$
2. Assign Pulse Frequency F_i
3. Define rate of pulse r_i and loudness parameter A_i
4. Initiate a loop, **while**$t <$ $Maximum\ number\ of\ iterations$, **do**
5. Update velocity iteratively and adjust frequency
6. Apply (9) to estimate HTF value
7. Apply (10) to update position value X_i
8. **If**$(rand > r_i)$**then**
9. Identify the G_{best} amongst the available sub-solutions across search space and update dimension of X_i arbitrarily as per the G_{best}'s dimensions
10. **end**
11. Generate new solutions arbitrarily
12. If $\left((rand > A_i)\ and\ F\left(X_i < F(G_{best})\right)\right)$, then
13. Chose the new solution by increasing pulse rate r_i and decreasing loudness A_i
14. **end**
15. Obtain G_{best} and rank the Bat in descending order.
16. **End**

The simulation results and allied inferences are discussed in the sub-sequent section.

III. Results and Discussion

In this research, focus is primarily on designing a classifier to classify different crowd videos to yield better performance. To perform crowd classification, the hybrid features [1] is applied to the BBA-MFNN classifier. In the proposed model, the hybrid features extracted from GLCM and Alexnet are directly fed as input neuron or input layer. Now, for modelling heuristic-based classifier, we assigned population size of 20, while the total number of generations as 1000. In addition, we assigned loudness factor - A and pulse rate as 0.5. The search dimension considered is 100, with reference to which the upper and lower bounds were obtained. To examine the performance of the proposed model, the terms True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are used to obtain the Confusion Matrix (CM). The mathematical model used to calculate accuracy, precision, recall and F-Measure is given in Table 1 [1].

Table 1. Performance Parameters [1]

Parameter	Mathematical Expression
Accuracy	$\frac{(TN+TP)}{(TN+FN+FP+TP)}$
Precision	$\frac{TP}{(TP+FP)}$
F-measure	$2.\frac{Recall.Precision}{Recall+Precision}$
Recall	$\frac{TP}{(TP+FN)}$

A. *Intra-Model Assessment*

The performance of the proposed crowd behaviour analysis and classification model is examined by employing different test conditions with different feature selection techniques and classification approaches. This is possible as in this paper we developed an EC (heuristic) assisted MFNN classification approach. To assess respective performance, we obtained CM for different features as well as classifier. At first, we examined the efficacy of GLCM and AlexNet CNN features with MFNN and BBA-MFNN distinctly. The statistical performance parameters obtained are given in Table II.

As depicted in Table II MFNN classifier with GLCM features which are primarily the statistical features such as energy, entropy, heterogeneity, dissimilarity, kurtosis and skewnessetc exhibits accuracy of 89.11%, precision (88.20%), recall (88.42%) and F-Measure of 88.30%, which is lower than the same with AlexNet-CNN features. In other words with AlexNet CNN, MFNN exhibits accuracy of 89.40%, precision 90.73%, recall 90.06% and F-Measure 90.40%. It exhibits that AlexNet-CNN based features are more efficient to yield higher accuracy and allied crowd analysis and classification performance. On the other hand, BBA-MFNN classifier exhibits 91.07% accuracy, precision of 90.12%, recall of 89.95% and F-Measure of 90.03% with GLCM features. On contrary the same classifier (i.e., BBA-MFNN) exhibits accuracy of 92.17%, precision of 94.28%, recall of 93.49% and F-Measure of 93.88% with AlexNet features, which is higher than both MFNN based classifier (with both features, GLCM as well as AlexNet) as well as GLCM feature based performance. It signifies that BBA-MFNN classifier can be a potential model to perform deep feature classification. Moreover, AlexNet CNN features can carry more significant features to yield higher accuracy and allied classification performance (Fig 2).

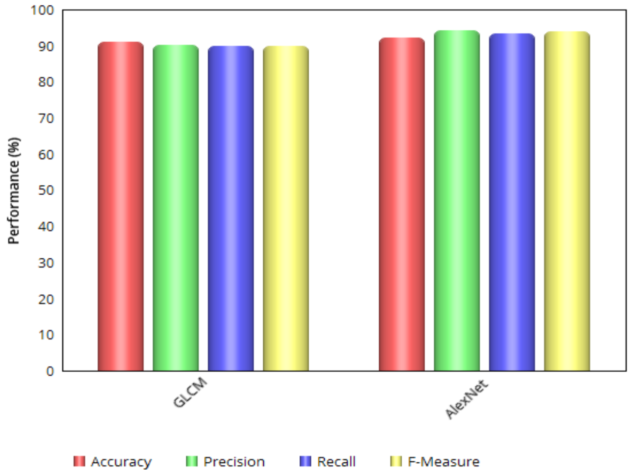

Fig. 2 Performance characterization with different features and classifiers

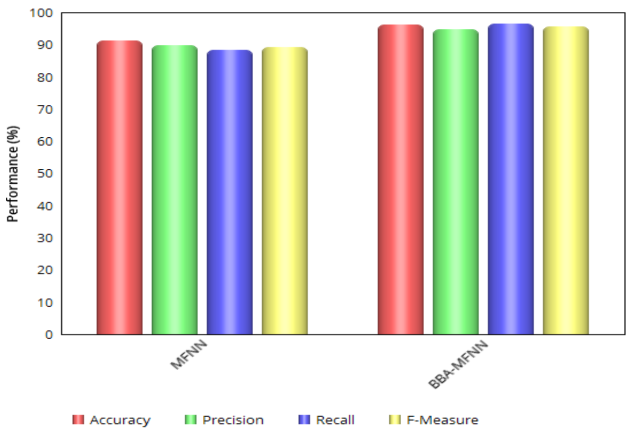

Fig. 3 Performance characterization with different classifier with hybrid deep features

Using hybrid features of [1] for classification, we studied the performance of our model. To analyse the performance of our model a comparative study of different crowd classifiers is carried out. Thus, we compared multi-class classification performance by both MFNN algorithm as well as BBA-MFNN, the EC assisted BBA classifier, which is given in Table III. Observing the results (Table

III and Fig. 3), it can be found that the maximum accuracy obtained by BBA-MFNN algorithm (96.15%) is higher than the classical feed-forward neural network or MFNN (91.35%). Similarly, the precision obtained by BBA-MFNN (94.66%) is almost 4.74% higher than the MFNN (89.92%) based classifier. Recall performance also affirmed that BBA-MFNN outperforms (96.52%) classical MFNN [1] based classier which could yield 88.3% sensitivity or recall. F-Measure performance by BBA-MFNN algorithm was found to be 95.56%, which was higher than MFNN classifier (89.12%). Thus, it tends to deduce that the proposed BBA-MFNN classifier model performs better than the MFNN based classifier with Hybrid Deep Features. However, AlexNet-CNN being more significant feature yields higher accuracy, and thus the hybrid features of GLCM and AlexNet CNN accomplishes better performance for analysis and classification of crowd behaviour. Thus, Hybrid Deep Feature (GLCM with AlexNet-CNN) with BBA-MFNN model yields better performance for crowd behaviour analysis and classification.

Table 2. Performance characterization with different features

Classifier	Accuracy		Precision		Recall		F-Measure	
	GLCM	AlexNet	GLCM	AlexNet	GLCM	AlexNet	GLCM	AlexNet
MFNN	89.11	89.40	88.20	90.73	88.42	90.06	88.30	90.40
BBA-MFNN	91.07	92.17	90.12	94.28	89.95	93.49	90.03	93.88

Table 3. Classifier Characterization with Hybrid Deep Features

Accuracy		Precision		Recall		F-Measure	
MFNN	BBA-MFNN	MFNN	BBA-MFNN	MFNN	BBA-MFNN	MFNN	BBA-MFNN
91.35	96.15	89.92	94.66	88.34	96.52	89.12	95.56

B. *Inter-Model Characterization*

We have performed inter-model performance characterization to assess the efficacy of the proposed model in comparison with the other approaches. Though, the data employed in this paper is different than the other researches, their performance or eventual classification performance has been compared.

Considering results in Table II and Table III, it can be found that BBA-MFNN based classifier achieves better performance than the classical MFNN algorithm. Eventually, considering overall results and allied observations it is found that the hybrid features including GLCM and AlexNet CNN with BBA-MFNN algorithm can achieve optimal performance towards crowd behaviour analysis and classification.

IV. Conclusion

We have proposed a robust and efficient model for video surveillance to analyse and classify crowd behaviour. Realizing the feature non-linearity and swift transition, where majority of the conventional machine learning algorithms might undergo local minima and convergence thus giving false result, an EC algorithm named Binary Bat Algorithm (BBA) based Multi Feed Forward Neural Network (BBA-MFNN) is developed which enabled optimal learning weight estimation and training. Unlike other classical heuristic models or EC algorithms, BBA is computationally more efficient and hence makes MFNN learning more swift and accurate. The proposed model performs multi-class classification for the various sorts of crowd such as Praying, Cheering, Praising, Quarrelling etc. The simulation results with different benchmark data shows that the proposed method accomplishes classification with an accuracy of 96.15%, precision of 94.66%, recall of 96.52% and F-Measure of 95.56%, which is higher than the classical MFNN classifier.

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