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A novel framework for Human Activity Recognition

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Abstract— Human activity recognition plays a competent part in human being to evaluate the activities of elder people. However, recently proposed human activity recognition techniques perform poorly whenever object characteristics are similar to background features (i.e., features are merely differing from each other). Therefore, an efficient meta-heuristic technique-based activity recognition technique is required to improve the accuracy of human activity recognition systems. To achieve the objectives of this research work, we have designed a novel hybrid differential evolution based J48 model to efficiently recognize the activities of human beings. Extensive experiments have been carried out to evaluate the effectiveness of the proposed technique. Experimental results reveal that the proposed technique outperforms existing techniques.

Keywords—Machine learning, Activity recognition, Differential evolution, Neural networks.

I. Introduction

Human activity recognition (HAR) is important for autonomous robot's interaction of with real world object, environment and people to further enhance its capabilities. Human activity recognition involves the interpretation of human actions or gesture from a series of human activities [1]. Daily human tasks can be simplified and automated if they are correctly recognized. Complex human activities can be subdivided into simpler ones which can later be combined to solve complex activity recognition problem [2]. For example, a domestic service robot for cleaning can recognize a sequence of activity as "sitting" followed by "standing" and "walking" (meaning the person has left the current environment) and discretionally clean up as a response to such combination of activities [3]. This has several applications in catering for needs of elderly people living alone or people with disability [4].

3D human action classification problems have been studied using various methods. Bayesian classifier has been used on multiple calibrated cameras for human gesture classification using motion history and energy volumes [5]. In [6] each gesture is decomposed into atoms and Hidden Markov Model (HMM) was used to identify their temporal evolution. Multi-Class AdaBoost algorithm was used in [7] together with dynamic programming algorithm for 3D joint feature processing and increased recognition accuracy. [8] Generic programming has also been used for human action recognition [8].

In this paper, we trained a convolutional neural network (CNN) to correctly classify human activities for recognition task [9]. The problem can be defined as: given an input of 3D human action sequence, the classifier should identify the sequence of activities performed from the kinematic data of human actions [10].

The objective is to correctly classify 3D human activities from kinematic data. As the first step to recognizing sequence of activities, a model for individual activity recognition task was first built. The goal is to combine individual human action for activity recognition for elder people recognition systems. Machine learning found applications in many fields such as genetics, natual language processing, search engines, computer vision, computational finance or stock market analysis. In the case of medical applications, the interest for learning-based methods seems more recent.

Nevertheless, this trend is increasing, and more works containing machine learning as keyword are published each year. Moreover medical imaging conferences such as MICCAI started to dedicate sessions and workshops to learning based approaches in medical imaging.

The rest of this paper is prearranged as follows: Section 2 refer to the mathematical model and parameters used; Section 3 describes the experimental set up, data and data preprocessing task; Section 4 argues the findings; finally, Section 5 concludes the paper.

II. Mathematical Preliminaries

Figure 1 shows sensor-based activity recognition techniques to predict the human activity.

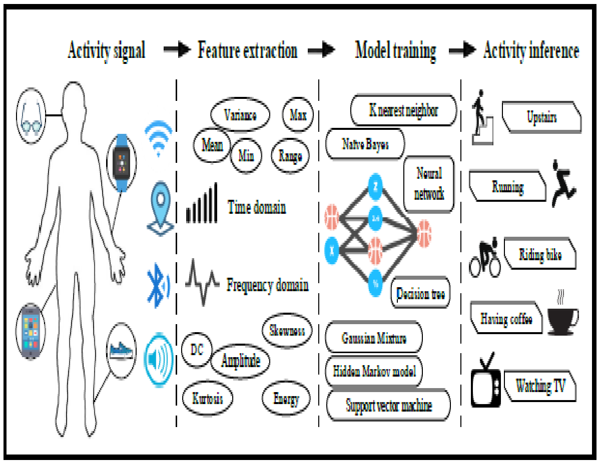

Figure 1. An illustration of sensor-based activity recognition using conventional approaches.

A. *Differential evolution*

Differential evolution is one of computational models stimulated together with the development and natural Selection processes. They design the most perfect option is together with the problem right information structure called chromosomes, genotype or genome signifying the wide ranging solutions, called individuals or creatures or phenotypes.

- Selection operator's makes using the evaluation function to find out what humans possess the biggest potential. They might persist whilst in the population and used with the other operators.
- The recombination operators (mutation and recombination) are traditionally utilized to produce new individuals using a few high potential individuals. They are designed to diversify the search process. The widely accepted operators of these kinds are recombination as well as mutation.
- The recombination operator uses 2 if not more fractions of high potential individuals to develop a fresh individual that's appended to your higher generation with all the population.
- The mutation operator, on contrary, takes one high potential individual as well as really a little alternation in amongst its components. The modern person is usually appended over the next generation with all the population.

III. Methodology:

A. *Proposed Algorithm*

The proposed work includes feature selection technique based differential evolution with various machine learning algorithms. The metrics vectors contain the form: $x_i G = [x_{1,i,G}, x_{2,i,G,...} x_{D,i,G}] = 1,2 \dots, N$ where G is the generation number.

Step.1: Initialization:

- Initialize upper as well as lower bounds for every metric:

$$x_j^L \leq x_{j,i,1} \leq x_j^L$$

- Arbitrarily choose the initial metric values consistently on the intervals $[x_j^L, x_j^L]$

Step.2: Mutation: Mutation is a process in which a bit involves flipping it, changing 0 to 1 and vice-versa. For example:

Before	0	1	1	1
After	0	1	0	1

- Every N metric vector go through mutation, recombination as well as selection.
- Mutation broad the search space.
- For a known metric vector x_{iG} arbitrarily choose three vectors x_{iG}, $xr2, G$, as well as $xr3, G$, for example which indices $i, r1, r2$ and $r3$ are different.
- Include the weighted variation of two of the vectors to the third $v_i, G+1 = x_r 1, +1G + (x_r 2, G - x_r 2, G)$
- The mutation factor F is a constant from [0, 2].
- $v_i G + 1$ Is called the donor vector.

Step.3: Recombination: Recombination is a process of taking more than one parent solutions and producing a child solution from them. For example:

Parent 1	A	B	C	D	E	F	G	H
Parent 2	H	G	F	E	D	C	B	A
Offspring	H	B	C	D	E	G	F	A

- Recombination incorporates achievable solutions from the previous generation.
- The trial vector u_iG+1 is constructed from the elements of the target vector, x_{iG} as well as the elements of the donor vector, v_iG+1
- Elements of the donor vector enter the trial vector with probability CR.

$$u_{ji}G+1 = \begin{cases} u_{ji}G+1 \; if Rand_{ji} \leq CRorj1_{rand} \\ x_{ji}G+1 if Rand_{ji} \neq CRorj1_{rand} \end{cases}$$

$i = 1,2 \dots \dots N; j\ 1,2, \dots \dots . D$

$Rand_{ji} \sim U[0,1] 1_{rand}$ is a random integer from [1, 2, . . . , D]

1_{rand} ensures that $u_{ji}G+1 \neq x_iG$

Step.4: Selection: Selection is a process that gives preference to improve individuals, permitting them to transfer their genes or individuals to a higher generation. The goodness of every individual is dependent upon its fitness. Fitness may be based upon goal function or using a subjective judgment.

- The target vector x_iG is associated with the trial vector v_iG+1 and the one with the deepest function value is admitted to the next generation

$$u_{ji}G+1 = \begin{cases} u_{ji}G+1 \; iff(u_{ji}G+1) \leq x_iG \\ i = 1,2, \dots \dots N \\ x_iG + 1 otherwise \end{cases}$$

- Mutation, recombination as well as selection continue unless number of stopping criterion is reached.

In proposed algorithm first it will check what the problem for which it will work is. Next we will collect the information that is required. We have collected activity recognition of elder individual information set from the respective site activity recognition of elder individual for activity recognition of elder individual classification and for recognition of the activity recognition of elder individual class.

In next step information selection and transformation is performed. Feature selection technique is helpful for selecting the desired attributes from the list of attributes. Once information set is loaded we apply the machine learning algorithms such as Naïve Bayes, Decision Table, and Random Forest etc. for activity recognition of elder individual classification.

IV. RESULTS AND DISCUSSION

A. *Evaluation parameters*

The evaluation measures which are used for testing the filters are defined as follow:

- **True Positive (TP):** It statuses the no of spam documents appropriately categorized as spam.
- **True Negative (TN):** It statuses the no of non-spam documents correctly classified as non-spam.
- **False Positive (FP):** It statuses the no of non-spam categorized as spam.
- **False Negative (FN):** It statuses the no of spam categorized as non-spam.
- **Accuracy:** It measures the fraction of emails that are correctly classified.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)}$$

- **Precision:** It gives the ratio between the number of emails that are correctly classified as spam and the number of emails classified as spam.

$$Precision = \frac{TP}{(TP+FP)}$$

- **Recall:** It measures the ratio between the no. of emails that are properly categorized as spam and the no of spam emails in the testing set.

$$Recall = \frac{TP}{(TP+FN)}$$

- F1-measure: It is a measure of test's accuracy. The optimal value of F1-measure is 1 and the worst value is 0.

$$F1-measure = \frac{2 * (Precision * Recall)}{(Precision + Recall))}$$

B. *Performance evalutaion*

When comparing the result of different approaches with Hybrid differential evolution (Hyb) we find Hyb results are better than the existing approaches. Table 1 illustrates results of the experiment for true positive and false positive (FP) of j48 before and after merging with differential evolution using human activity dataset. Comparative study of the different methods has been graphically represented in Figure 3. The true positive rate and false positive rate using j48 for testing are 0.944% and 0.092%, final results after using Hyb reduce false positive rate and improve true positive rate.

Table 1. Comparative analysis of True Positive and False Positive Result of proposed with different methods

Algorithm	TP	FP
Naïve bayes	0.839	0.279
J48	0.944	0.092
Random tree	0.909	0.096
Random forest	0.948	0.065
LMT	0.898	0.124
Logistic	0.924	0.089
K Star	0.91	0.113
Bagging	0.94	0.071
Hyb	0.985	0.048

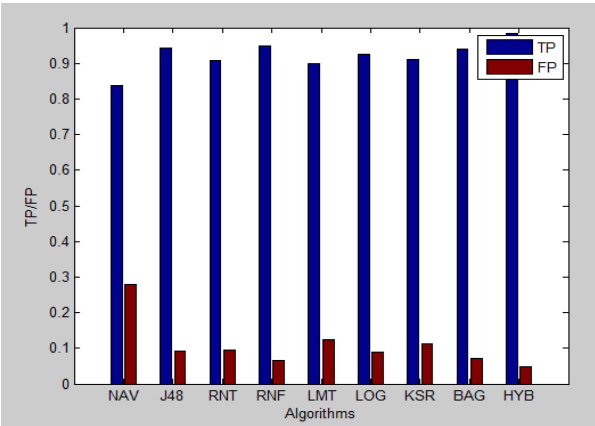

Figure 2. A true positive rate and false positive rate comparisons between different methods

Table 2 shows the outcomes of the testing for precision, recall and f-measure of j48 before and after merging with differential evolution and also with other methods using human activity dataset. Figure 4 presents the precision, recall and f-measure comparisons between different methods.

Table 2. Comparative analysis of precision, recall and F-measure result of proposed method with different methods

Algorithm	Precision	Recall	F-Measure
Naïve bayes	0.822	0.839	0.83
J48	0.94	0.944	0.942
Random tree	0.91	0.909	0.91
Random forest	0.948	0.948	0.948
LMT	0.898	0.898	0.897
Logistic	0.924	0.924	0.924
Kstar	0.91	0.91	0.909
Bagging	0.94	0.94	0.94
Hyb	0.969	0.985	0.977

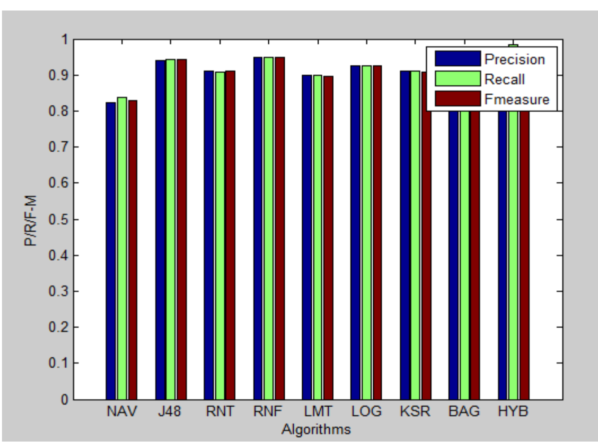

Figure 3. A Precision, recall and F-measure comparisons between different methods

Classification using Hyb is at its best 97.1745% of accuracy while for J48 only accuracy is 92.9798% as shown in Table 3. Figure 4 represents the final results after using Hyb which improve the accuracy, reduce the error rate and give a better result than the others.

Table 3. Comparative analysis of accuracy and error rate results of proposed with different methods

Algorithm	Accuracy	Error rate
Naïve bayes	79.246%	20.754
J48	92.9798%	7.0202
Random tree	90.9368%	9.0632
Random forest	94.7837%	5.2163
LMT	89.8066%	10.1934
Logistic	92.414%	7.586
Kstar	90.9585%	9.0415
Bagging	94.0013%	5.9987
Hybrid	97.1745%	2.8255

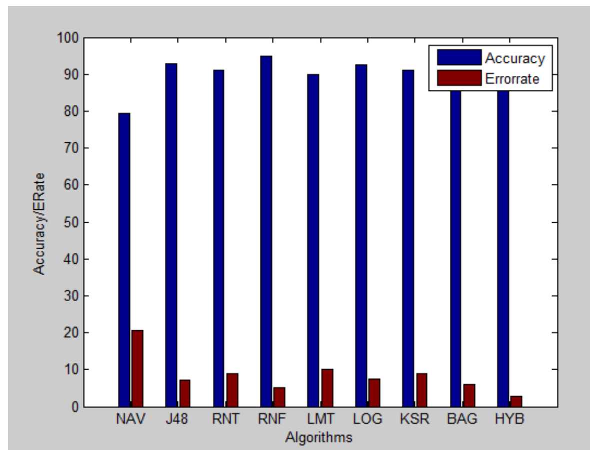

Figure 4. Accuracy and error rate comparisons between different methods

V. CONCLUSION and Future Scope

The Individual action appreciation is a vital enquiries issue in machine learning. In this paper, we studied the current developments in sensor-based action appreciation. Associated to outmoded machine learning techniques, machine learning decreases the need on individual-crafted feature abstraction and realizes improved enactment by mechanically learning high-level illustrations of the sensor data. Our activity recognition model was accomplished and verified on the publicly available Vicon physical action dataset used for mobile robot. We also carried out our own experiment to validate the accuracy of the trained model by generating 6 different activity data. The simulation outcomes have presented that the proposed method overtakes over the existing methods.

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