International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Range Specific Neighborhood Rough Set Based Feature Selection for Driver Inattention Classification

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***Abstract:** In the view of performance improvement in machine learning algorithms it is essential to feed them with relevant features. Feature selection is one of the evident process followed by most of the learning algorithms for choosing the relevant features towards reducing the dimensionality of the dataset as well as to improve the classification accuracy. Among various feature selection techniques, Rough Set Theory (RST) has its own major contributions to feature selection domain. However, the conventional rough set based feature selection procedure makes binary decision on either marking an attribute as relevant or irrelevant.The fuzzy based Rough Set could resolve this problem by finding the relevancy by using membership values, however, this method is unable to identify the boundary or range of an attribute value which is appropriate for classification. The idea of feature selection is inappropriate when specific range of an attribute value represents a decision variable while seems to be irrelevant when it's complete range is considered. This research work focuses on choosing relevant features for the problem of driver inattention detection. The features extracted for the focused problem are real numbers, hence the Neighborhood Rough Set (NRS) model is followed here rather than conventional Rough Set(RS) approach. In this paper, a Range specific Neighborhood Rough Set (RNRS) based feature selection is proposed for more accurate feature selection for the application of detecting driver's inattention problem. The experiments are carried out with three real time driver datasets and the results are reported to prove the significance of the proposed RNRS based feature selection. Two learning algorithms, namely K-nearest neighbors and support vector machines are usedto evaluate the performance of the proposed approach. Theresults show that the proposed algorithm can significantlyimprove the classification performance.*

***Keywords:** Range specific Neighborhood Rough Set (RNRS), Driver inattention, support vector machine, K-nearest neighbors.*

I. INTRODUCTION

Safe driving is a global factor to avoid accidents and mortality rate. Most of the accidents were happened due to drivers' inattention, falling asleep at the wheels.

Manuscript published on November 30, 2019.
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Recent survey indicate that 20% of the road accidents were claimed that the drivers' inattention and their ability of controlling vehicles (Hu & Zheng, 2009). Therefore, it is evident to construct a safety system to alert the drivers' inattention to avoid the accidents.

Drivers' inattention is mentioned as any secondary action performed by drivers other than driving related activities. A national study depict that, in the overall, 16.1% time the drivers are inattentive, and 30% of them are using mobile phones while driving. There are three major factors identified as affecting drivers' attention,

- Much driving task, where the drivers' would be unable to balance their cognitive and physical workload.
- Distraction, it might be calls, signs, or passengers from physical mode, cognitively the distractions could happen through worry, anxiety, aggression, etc.
- Misjudgment or inexperience, due to superior thought and over confidence the road mishap could happen.

These factors indicate that the simply following the traffic rules alone is not be enough, the attention of the drivers' make more sense. There are many parameters have been suggested to measure the driver attention based on physiological, environmental and vehicular data.Akerstedt&Gillberg, (1990) presented the inattention or drowsiness on two different scores like Karolinska Drowsiness Score (KDS), Karolinska Sleepiness Scale (KSS). Theoretically, a classification system with more features would be a more generalized model, however, if the number of features is too high then the complexity of training phase will increase as well as there is chance that the classification model may divergent. Hence, it is necessary to identify the relevant features, called as dimension reduction or feature selection techniques. A novel rough set based feature selection approach, Range specific Neighborhood Rough Set (RNRS) is proposed in this paper for choosing relevant features for the driver inattention detection problem.

The rest of the paper is organized as follows: the following section summarizes the feature selection methods applied so far in driver inattention recognition context. Section 3 presented the fundamentals for rough set based feature selection. Section 4 explains the proposed RNRS based feature selection. Section 5 discusses the experimental setup, where the feature extraction methods are presented. Results are quantified and analyzed in Section 6, and Section 7 concludes the paper.

II. RELATED WORKS

Torkkola et al., (2008) extracted the Collision Avoidance Systems (CAS) sensors based features for driver inattention detection, where the feature relevance is identified using Random Forest (RF) method. González-Ortega et al., (2008) proposed a driver alertness monitoring system with PERCLOS (percentage of time eyelids are close) based histogram features, where the sequential forward approach is used to select relevant features. Most of the driver monitoring system focuses on single eye lid movement features, however these systems might suffer from low robustness and lower accuracy. Hu & Zheng (2009) proposed the feature set with both eye lid movements and its relation with degree of drowsiness. Here, paired t-test is used for feature selection. Vural et al., (2009) proposed a driver drowsiness detection system based on video features, here the feature dimension is reduced by using Multinomial Ridge Regression (MLR) method.

Du et al., (2010) proposed a Kernelized Fuzzy Rough Set (KFRS) based feature subset selection to identify candidate features to estimate driver drowsiness. Siordia et al., (2010) presented a multidisciplinary system for automatic driver risk level classification based on driver, road and vehicle features. The feature selection is achieved through ReliefF (Robnik-Šikonja&Kononenko, 2003) algorithm. Friedrichs& Yang (2010) reduce the feature dimension using Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA) methods, followed by applying Sequential Floating Forward Selection (SFFS) algorithm. Kircher& Ahlstrom (2010) also applied SFFS algorithm for feature selection and reported that stochastic optimization methods would generate better feature subset. Tawari & Trivedi (2011) presented a driver monitoring system based on speech signals. Here, a set of 137 acoustic features were extracted initially then it was reduced to a set of 20 features by using Sequential Forward Selection (SFS) method. Rahman et al., (2011) proposed an automatic sleepiness detection system based acoustic features. The feature set dimension is reduced to different values using a chi-squared test based feature selection method. Rigas et al., (2011) proposed a drivers' stress and fatigue detection system with set of features like ECG, EDA, face and environmental data. A metric called Difference in the Area Under the Curve (D-AUC) is used to measure the features' relevance, and their classification performance is studied with classifiers like SVM, Decision Trees, and Naïve Bayes. The results indicate that D-AUC metric based feature selection outperforms other SFS methods.

Sahayadhas et al., (2012) has studied vehicle, behavioral, and physiological-based measures to determine driver drowsiness. The conclusion says that a combination of these methods would be able to determine drivers' drowsiness better than individual features. And reported that the vehicle-based measures are unreliable, behavioral measures are subject to lighting conditions and physiological measures are intrusive as limitations of the measures. Sathyanarayana et al., (2012) proposed a driver assistance system by using portable Controller Area Network (CAS)-bus signals. The result indicate that the portable sensors could improve the driver behavior model. Li &Busso (2013) proposed a driver distraction classification system based on action units and gaze features, which consists of 186 features in total. Forward Feature Selection (FFS) methods is used to choose 30 most relevant features and reported a classification average of 80.8%. Li & Chung (2013) proposed a driver inattention monitoring system based on Fast Fourier Transform (FFT) based features where the relevant features are identified using Receiver Operating Characteristic (ROC) curve. The results reported with the maximum of 95% accuracy. Begum (2013) presented a study on various physiological sensor signals for intelligent driver monitoring system. And reported that feature selection using kernel-based class separability (KBCS) outperforms other feature selection methods in drivers' drowsiness monitoring systems. Most of the time PCA based feature selection results in low accuracy as it doesn't consider the class labels. However, LDA based feature selection depends on appropriate regularization or pre-processing step. Recently, Orthogonal Fuzzy Neighborhood Discriminant Analysis (OFNDA) has been proposed for feature selection and report that it outperforms PCA and LDA. However, OFNDA also requires PCA or regularization as a preprocessing step.

Khushaba et al., (2013a) proposed an advanced version of OFNDA known as FNDA, where QR decomposition is used as preprocessing rather than PCA or regularization step, which improves the driver distraction detection as reported in the results section. González-Ortega et al., (2013) proposed a drivers' fatigue measurement system using PERCLOS and facial features. Here the SFS method is used for feature selection. This system is able to achieve the maximum of 96.22% of classification accuracy. Khushaba et al., (2013b) presented a drivers' fatigue detection systems using physiological features like Electroencephalogram (EEG), Electrooculogram (EOG) and Electrocardiogram (ECG) signal. The feature selection performed with Singular Value Decomposition (SVD) method, followed by Fuzzy Neighborhood Preserving Analysis (FNPA) based classification. This system has reported an accuracy of 93%. Mbouna et al., (2013) make use of eye and head movement based visual features to classify driers' alertness. The t-test is used to rank the features, and the SVM classifier reports better results for this proposed system.

Robinel&Puzenat (2014) proposed a driver action monitoring system based on behavioral features. These features are reduced based SFS method and classified with Support Vector Machine (SVM) classifier. The experimental results indicate the significance of feature selection process. Singh et al., (2014) employed the combination of filter and wrapper based feature selection methods. Here the variance filter and entropy filter, Sequential Forward Selection (SFS) and Sequential Backward Selection methods are applied over a feature set with 39 features, which is further reduced to 30 features. Correa et al., (2014) proposed an automatic driver drowsiness detection system using a set of 19 EEG features, where LDA is used for feature selection. Darshana et al., (2014) presented an automatic driver inattention alter system based on PERCLOS and gaze features with LSVM classifier, where SFS method is used for feature selection.

Zhu et al., (2014) proposed a drivers' drowsiness detection system with EOG signal based features. Here a Linear Dynamic System (LDS) is proposed for feature selection, and Convolutional Neural Network (CNN) is used as a classifier. Hari &Sankaran (2014) presented a driver distraction monitoring scheme, where LDA is used for facial feature selection.

Li et al., (2014) presented a multi-sensor based driver drowsiness detection system, where the relevant features are identified using SFS method. Li &Busso (2014) employed visual and cognitive based multimodal features for driver distraction classification system. The investigation results state that the multimodal features are significantly improving the classification results. Fridman et al., (2015) presented a driver assistance system based on their gaze features, where the Delaunay triangulation method is used for feature selection.

Koesdwiady et al., (2015) presented a driver monitoring system with PCA based feature selection followed by Random Forest (RF) based classification, and reported a maximum accuracy of 91.46% for a minimal sample of data. Harsham et al., (2015) developed a driver action prediction system based on speech signals, where SFS method is used for feature selection. Braunagel et al., (2015) implemented a Fact Correlation Based Filter (FCBF) algorithm for dimensionality reduction in driver-activity recognition context with eye and head based features. Guo et al., (2015) proposed a driver fitness assessment system, where PCA was applied for feature selection. Jalilifard et al., (2016) presented a k-Nearest Neighbor (kNN) based driver drowsiness detection system with EEG features. Random Forest algorithm is used to choose more relevant features, in which the original set of 52 features were reduced to 11, and reported a classification accuracy of 91%. Bixler&D'Mello (2016) proposed a user alertness detection system based on gaze features, were the relevant features are identified with Correlation-based Feature Selection (CFS) method. Liao et al., (2016) proposed a driver distraction identification system based on eye movement. Here the SVM-Recursive Feature Elimination (SVM-RFE) is used feature selection and SVM is used for classification. The result indicate the significance performance improvement with the maximum accuracy of 95.8%. Fridman et al., (2016) presented a driver gaze recognition system based on facial features, where Recursive Feature Elimination (RFE) method is used for dimensionality reduction. Alioua et al., (2016) proposed a driver attention level estimation system based on head pose. The feature descriptors used here are steerable filters, Histogram of Gradients (HOG), and the Haar features. A comparative study was performed between three feature selection algorithms like Best First, Greedy and Ranker, where the Greedy based feature selection algorithm achieves better classification accuracy than the other. Alizadeh&Dehzangi (2016) presented a driver fatigue detection system based on EEG features, where the feature dimension is reduced with SFS method.

Melnicuk et al., (2016) conducted a review over driver assistance monitoring systems and reported that the merits of integrating them as an in vehicle device. Vasudevan et al., (2017) developed a driver monitoring and warning system based on vehicle parameters, where the feature relevance is identified by p-value estimated from an Analysis of Covariance (ANOVA). Also the performance of various classifiers such as RF, MLP and SVM are studied and reported that SVM based classification was able to achieve better accuracy than the other classifiers. Deshmukh&Dehzangi (2017) predicted the driver distraction with ECG signal. Here the features extracted using Wavelet Packet Transform (WPT), which is further reduced by applying PCA. Hari &Sankaran (2017) developed a driver distraction system based on environmental features, where PCA and LDA are used for feature selection. Xing et al., (2017) proposed a driver behavior recognition system based on physiological features, where the feature relevance computed using a measure called. Maximum Information Coefficient (MIC). Rastgoo et al., (2018) conducted a survey on driver stress detection system based on multimodal features, and discussed that feature selection step is necessary towards improving the classification accuracy in this context. Majdi et al., (2018) proposed a driver distraction detection using Convolutional Neural Network (CNN) with HoG features, where PCA was applied for dimensionality reduction.

Jeong et al., (2018) presented a driver assistance system based on facial landmark features, where the feature dimension is reduced with Correlation based Feature Selection (CFS) method. Sikander& Anwar (2018) studied driver fatigue detection systems and reported that hybrid features were performing better than independent features. Du et al., (2018) proposed a driving fatigue detection system based on facial features. A Kernelized Fuzzy Rough Sets (KFRS) was used to identify relevant features from the set of 50, which is further reduced to 15. Chaudhuri &Routray (2019) presented a diver fatigue recognition system based on EEG data, where ReliefF algorithm is used for feature selection. The results shown that this system is able to achieve 86% of classification accuracy. Dehzangi&Taherisadr (2019) presented a driver inattention identification system based on EEG features, where LDA is applied for reducing the feature dimension. In driver fatigue detection context, Panda &Kolhekar (2019) compared the performance of various feature extraction techniques such as canny edge, Local Binary Pattern (LBP), HOG and Gabor filters with SFS based feature selection method. The experimental results indicate that HOG features improves the classification accuracy than any other set of features.

III. NEIGHBORHOOD ROUGH SET BASED FEATURE REDUCTION

Dimensionality reduction is a common method used in pattern recognition, machine learning and data mining applications. This is due to the high volume of data storage, considering the whole features for the learning algorithms might slowdown the process, moreover this excessive amount of features may leads to over-fitting problem. Hence, it is necessary to identify and remove the irrelevant and redundant features from the database. There are three major techniques available for feature selection such as filter, wrapper and embedded.

Further the feature selection algorithms could be categorized into two based on type of data: symbolic and numerical, the former category considers that all features are categorical variables, while the later consider the attributes of real values. In general, the real-valued data are discretized to partition them into intervals, and processed as symbolic values. Discretization of numerical features may leads to information loss because the degrees of membership of real values to discretized values are not considered (Ching et al., 1995; Jensen & Shen, 2004). Moreover, the neighborhood structure and order structure would be lost due to discretization. For illustration, the distance between two data sample in real space could not be retained after discretization. Though this issue could be handled by heterogeneous distance functions as discussed in Wilson & Martinez (1997) and Wang (2006), such methods have not been fully studied so far (Tang & Mao, 2007).

Rough Set (RS) theory, proposed by Pawlak(2012), has been proven to be an effective tool for feature selection from categorical data in recent years. Shen & Jensen presented a Fuzzy-Rough Set to handle real valued data, however the complexity of the algorithm is high, and generating effective fuzzy relations in various problem space is also an open problem (Yeung et al., 2005). Hu et al., (2008) introduced a Neighborhood Rough Set (NRS) model to perform feature selection with heterogeneous (categorical and numerical) attributes. The conventional rough set model given by Pawlak (2012), estimates the equivalence relation to divide the universe and produce mutually exclusive equivalence classes as primary objects. Thus, RS theory is applicable for nominal attributes. Whereas the neighborhood relations can be used to generate a set of neighborhood granules from the universe characterized with numerical attributes, further the granules can be used to approximate decision classes. In other way, the neighborhood model can be thought of a natural generalization of conventional rough set theory. The following text describes the concept of NRS as illustrated in Hu et al., (2008).

3.1 Neighborhood Rough Sets (NRS)

In general, the data samples used for classification can be known as an information system, represented by $I = \langle U, A\rangle$, where U is a nonempty and finite set of samples $\{x_1, x_2, \dots, x_n\}$ called a universe, A is a set of attributes $\{a_1, a_2, \dots, a_m\}$ to characterize the samples. In specific, the information system can also be called as a decision table if $A = C \cup D$, where C is the set of condition attributes and D is the decision attribute. Given arbitrary $x_i \in U$and $B \subseteq C$, the neighborhood $\delta_B(x_i)$ of x_i is defined as

$$\delta_B(x_i) = \{x_j | x_j \in U, \Delta^B(x_i, x_j) \leq \delta\}$$

whereΔ is a distance function. For $\forall x_1, x_2, x_3 \in U$, it usually satisfies:

(i) $\Delta(x_1, x_2) \geq 0, \Delta(x_1, x_2) = 0\ if\ and\ only\ if\ x_1 = x_2;$

(ii) $\Delta(x_1, x_2) = \Delta(x_2, x_1);$

(iii) $\Delta(x_1, x_3) \leq \Delta(x_1, x_2) + \Delta(x_2, x_3)$

There are three distance functions extensively applied in machine learning. Considered that $x_1$and x_2 are two objects in N-dimensional space, $A = \{a_1, a_2, \dots, a_N\}, f(x, a_i)$ denotes the value of sample x in the ith attribute a_i, then a common measure called Minkowski distance is defined as

$$\Delta_P(x_1, x_2) = \left(\sum_{i=1}^{N} |f(x_1, a_i) - f(x_2, a_i)|^P\right)^{1/P}$$

The same formula can be used to measure other distance metric by changing the P value, if P=1, then the equation estimates the Manhattan distance (Δ_1), Euclidean distance (Δ_1) if P = 2, and Chebychev distance if $P = \infty$.

$\delta_B(x_i)$represents the neighborhood relation centered with sample x_i and the size of the relation is based on threshold δ. The greater value assigned for δ allows more sample to fall into the neighborhood, and the shape of the neighborhoods depend on the used norm. It's shown that the neighborhood relations depends on two key factors such as distance metric and the threshold value. The distance metric defines the shape and the threshold value defines the size of the neighborhood. Suppose if the threshold is set with zero, which simulates the classical Pawlak's rough set theory. Though the NRS is handle heterogeneous sample of data, here for driver inattention detection, the features are only real numbers. Hence the following text describes the NRS by considering the real data alone.

Definition 1. Let $B \subseteq A$ be numerical attributes, the neighborhood relation of sample x induced by B is defined as

$$\delta_B(x) = \{x_i | \Delta_B(x, x_i) \leq \delta, x_i \in U\}$$

Based on this definition, the samples in a neighborhood relation have the distance which are less than threshold δ.

Given an information system $\langle U, A\rangle$ and $C_1 \subseteq A$ and $C_2 \subseteq A, \delta$ is a positive number. The neighborhood relation N_δ^C with Chebychev distance and δ is defined as

$$N_\delta^{C_1 \cup C_2} = N_\delta^{C_1} \cap N_\delta^{C_2}$$

Let us assume that $x_i, x_j \in U$, the distance between these samples is $\Delta^C(x_i, x_j) = \max|f(x_i, a) - f(x_j, a)|$ as to Chebychev distance and features C. At the same time the distance should be less than the threshold at both C_1 and C_2. Based on this discussion, the neighborhood relation could be estimated for each attribute independently and the intersection of such relations is the relation prompted with the union of two subsets of features. This characteristics is useful in constructing forward feature selection algorithms, where the first iteration should estimate the neighborhood relations for each feature independently, followed by computing the relations with the combination of features from the dataset.

Given a set of objects U and a neighborhood relation N over U, the neighborhood approximations for any subset of objects $X \subseteq U$, are defined as

$$\underline{N}X = \{x_i | \delta(x_i) \subseteq X, x_i \in U\},$$
$$\overline{N}X = \{x_i | \delta(x_i) \cap X \neq \emptyset, x_i \in U\}$$

It is given that, $\underline{N}X \subseteq X \subseteq \overline{N}X$, where the boundary region of X in the approximation space is defined as

$$BNX = \overline{N}X - \underline{N}X$$

The size of the boundary region reflects the degree of roughness of set X in the approximation space $\langle U, N\rangle$. Assuming X is the sample subset with a decision label, the size of the boundary region is
based on U and threshold.

Table 1. Sample dataset

Object	a	b	D
1	0.85	0.71	N
2	0.51	0.58	Y
3	0.54	0.74	N
4	0.57	0.69	Y
5	0.50	0.60	Y
6	0.82	0.80	N

For an illustration, considering the dataset given in Table 1 consisting of numerical values a & b and D is the decision attribute. Let's compute the neighborhood relations with the threshold value $\delta = 0.1$. For the attribute a the neighborhood relations are estimated as

$$\delta_a(x_1) = \{x_1, x_6\}, \delta_a(x_2) = \{x_2, x_3, x_4, x_5\}, \delta_a(x_3) = \{x_2, x_3, x_4, x_5\},$$

$$\delta_a(x_4) = \{x_2, x_3, x_4, x_5\}, \delta_a(x_5) = \{x_2, x_3, x_4, x_5\}, \delta_a(x_6) = \{x_1, x_6\}$$

Similarly, for the b attribute, the neighborhood relations with the same threshold are

$$\delta_b(x_1) = \{x_1, x_3, x_4, x_6\}, \delta_b(x_2) = \{x_2, x_5\}, \delta_b(x_3) = \{x_1, x_3, x_4, x_6\},$$

$$\delta_b(x_4) = \{x_1, x_3, x_4, x_5\}, \delta_b(x_5) = \{x_2, x_4, x_5\}, \delta_b(x_6) = \{x_1, x_3, x_6\}$$

Further, the samples are grouped based on the decision attribute as two subsets:

$$X_1 = \{x_1, x_3, x_6\} \text{ } and \text{ } X_2 = \{x_2, x_4, x_5\}$$

Now, the lower and upper approximation upon attribute a is estimated as

$$\underline{N}X_1 = \{x_1, x_6\} \text{ } and \text{ } \overline{N}X_1 = \{x_1, x_2, x_3, x_4, x_5, x_6\}$$

$$\underline{N}X_2 = \{\emptyset\} \text{ } and \text{ } \overline{N}X_2 = \{x_2, x_3, x_4, x_5\}$$

In the same way, the lower and upper approximation over attribute b is given as

$$\underline{N}X_1 = \{x_6\} \text{ } and \text{ } \overline{N}X_1 = \{x_1, x_3, x_4, x_6\}$$

$$\underline{N}X_2 = \{x_2, x_5\} \text{ } and \text{ } \overline{N}X_2 = \{x_1, x_2, x_3, x_4, x_5\}$$

The neighborhood relation between the attributes a & b can be computed as follows

$$\delta(x_1) = \delta_a(x_1) \cap \delta_b(x_1) = \{x_1, x_6\} \cap \{x_1, x_3, x_4, x_6\} = \{x_1, x_6\}$$

$$\delta(x_2) = \delta_a(x_2) \cap \delta_b(x_2) = \{x_2, x_3, x_4, x_5\} \cap \{x_2, x_5\} = \{x_2, x_5\}$$

$$\delta(x_3) = \delta_a(x_3) \cap \delta_b(x_3) = \{x_2, x_3, x_4, x_5\} \cap \{x_1, x_3, x_4, x_6\} = \{x_3, x_4\}$$

$$\delta(x_4) = \delta_a(x_4) \cap \delta_b(x_4) = \{x_2, x_3, x_4, x_5\} \cap \{x_1, x_3, x_4, x_5\} = \{x_3, x_4, x_5\}$$

$$\delta(x_5) = \delta_a(x_5) \cap \delta_b(x_5) = \{x_2, x_3, x_4, x_5\} \cap \{x_2, x_4, x_5\} = \{x_2, x_4, x_5\}$$

$$\delta(x_6) = \delta_a(x_6) \cap \delta_b(x_6) = \{x_1, x_6\} \cap \{x_1, x_3, x_6\} = \{x_1, x_6\}$$

With the given neighborhood relations, the lower and upper approximations of X_1 and X_2 are given as

$$\underline{N}X_1 = \{x_1, x_6\} \text{ } and \text{ } \overline{N}X_1 = \{x_1, x_3, x_4, x_6\}$$

$$\underline{N}X_2 = \{x_2, x_5\} \text{ } and \text{ } \overline{N}X_2 = \{x_2, x_3, x_4, x_5\}$$

The lower approximation of the decision is given as the union of the lower approximation of each decision class, which is also known as the positive region of the decision, denoted by $POS_B(D)$, is the subset of objects whose neighborhood granules consistently belong to one of the decision classes.

Given a neighborhood decision table $\langle U, C \cup D, N \rangle$, distance function Δ, and threshold value δ, the attribute dependency degree of D to B is defined as

$$\gamma_B(D) = \frac{|POS_B(D)|}{|U|}$$

Where $|.|$ is the cardinality of the set, $\gamma_B(D)$ reflects the ability of B to approximate D. As $POS_B(D) \subseteq U$, we have $0 \leq \gamma_B(D) \leq 1$. This inference says that D completely depends on B and the decision system is consistent in terms of Δ and δif $\gamma_B(D) = 1$; otherwise, D depends on B in the degree of γ.

The dependency degree could be used to measure the relevance of a subset of attributes, hence it is used for feature selection in rough set theory. This section describes the measure for attribute evaluation and the basic method of neighborhood based feature selection. Given a neighborhood decision system $\langle U, C \cup D, N \rangle, B \subseteq C, \forall a \in B$, the significance of a in B is defined as

$$S(a, B, D) = \gamma_{B \cup a}(D) - \gamma_B(D), \forall a \in A - B$$

It is noted that the significance of an attribute depends on three variables: a, B and D. An attribute a may be of great significance in one subset but of little significance in another. Moreover, the significance of an attribute differs for each decision class.

The main objective of rough set based feature selection is to identify a subset of features which has the same discriminating power as the original data and has not any redundant attribute. Although there usually are multiple reducts for a given decision table, in the most of applications, it is enough to find one of them. With the presented metrics, a forward greedy search algorithm for feature selection can be expressed as follows:

Algorithm 1 – Forward Feature Selection based on Neighborhood Rough Set (NRS) model.

Input: $\langle U, C \cup D, f \rangle$ *and* δ

Output: R → the reduct, contains selected attributes

1. $R \leftarrow \emptyset$
2. **for** each $a_i \in C - R$
    a. Compute $\gamma_{R \cup a_i}(D) = \frac{|POS_{B \cup a_i}(D)|}{|U|}$
    b. Compute $S(a_i, R, D) = \gamma_{R \cup a}(D) - \gamma_R(D)$
3. **end**
4. Select the attribute a_k satisfying $S(a_k, R, D) = \max_i\left(S(a_i, R, D)\right)$
5. **if**$S(a_k, R, D) > \epsilon$, ϵ is the small positive number used to control the convergence
    a. $R \leftarrow R \cup a_k$
    b. goto Step-2
6. **else**
    a. return R
7. **endif**

IV. RANGE SPECIFIC NEIGHBORHOOD ROUGH SET BASED FEATURE REDUCTION

Hu et al., (2008) shown that the Neighborhood Rough Set (NRS) model based feature selection with numerical or heterogeneous attributes, outperforms other feature selection methods. However, in sometimes the whole range of a numerical attribute may not seems to be relevant, but a portion of it seems to be relevant. Considering the sample dataset given in Table 1, based on decision attribute the attribute ‘a’ has two set of values as given in the last column of Table 2.

Table 2. Range of Numerical Attribute ‘a’ from sample dataset

Object	a	D	Range
3	0.54	N	0.54 to 0.85
6	0.82	N	
1	0.85	N	
5	0.50	Y	0.50 to 0.57
2	0.51	Y	
4	0.57	Y	

As given in Table 2, there is an overlap between the numerical ranges upon decision classes. For example, a value of 0.55 can’t be precisely labelled either with ‘N’ or ‘Y’ label. However, for the ‘b’ attribute there is no such problem as depicted in Table 3.

Table 3. Range of Numerical Attribute ‘b’ from sample dataset

Object	b	D	Range
1	0.71	N	0.71 to 0.80
3	0.74	N	
6	0.80	N	
2	0.58	Y	0.58 to 0.69
5	0.60	Y	
4	0.69	Y	

In this paper, a novel Range specific Neighborhood Rough Set (RNRS) method is proposed to solve this issue. For the proposed RNRS method, the feature dependency degree is estimated at different range of intervals, among them the one range which has higher dependency degree is chosen for the reduct. Hence the reduct set not only maintains the relevant attribute set, in addition, the relevant range also stored for each element of the set.

Given a neighborhood decision table $\langle U, C \cup D, N \rangle$, distance function Δ, and threshold value δ, the attribute dependency degree of D to B is defined as

$$\psi_B(D) = \frac{|POS_B(D)|}{|U|}, where\ B \subseteq C, B = \{x_k^{[l_k, u_k]}\}$$

Where, l_k *and* u_k, represents the lower and upper range of the object x_k. There is a chance of getting more ranges for a particular attribute. Hence, for the proposed NRNS based algorithm it is necessary to find numerical attributes’ range for each class label and eliminate the range which has overlap. Based on this discussion, for the same sample dataset, the neighborhood relations with the threshold value 0.1 are estimated as follows:

For the conditional attribute ‘a’ the object x_3 causes the overlap with the value 0.54, hence the ranges are trimmed to not to allow this value. The trimmed ranges are given in Table 4.

Table 4. Trimmed ranges of Numerical Attribute ‘a’ from sample dataset

Object	a	D	Range
3	0.54	N	0.82 to 0.85
6	0.82	N	
1	0.85	N	
5	0.50	Y	0.50 to 0.51
2	0.51	Y	
4	0.57	Y	

Further the neighborhood granules are calculated within this trimmed ranges. In this way, the objects 3 and 4 won’t be part of any relations. The range specific neighborhood relation for the attribute ‘a’ is given as

$\delta_a(x_1) = \{x_1, x_6\}, \delta_a(x_2) = \{x_2, x_5\}, \delta_a(x_3) = \{x_2, x_5\},$
$\delta_a(x_4) = \{x_2, x_5\}, \delta_a(x_5) = \{x_2, x_5\}, \delta_a(x_6) = \{x_1, x_6\}$

$$\delta_b(x_1) = \{x_1, x_3, x_4, x_6\}, \delta_b(x_2) = \{x_2, x_5\}, \delta_b(x_3) = \{x_1, x_3, x_4, x_6\},$$
$$\delta_b(x_4) = \{x_1, x_3, x_4, x_5\}, \delta_b(x_5) = \{x_2, x_4, x_5\}, \delta_b(x_6) = \{x_1, x_3, x_6\}$$

The neighborhood relation between the attributes a & b can be computed as follows

$$\delta(x_1) = \delta_a(x_1) \cap \delta_b(x_1) = \{x_1, x_6\} \cap \{x_1, x_3, x_4, x_6\} = \{x_1, x_6\}$$
$$\delta(x_2) = \delta_a(x_2) \cap \delta_b(x_2) = \{x_2, x_5\} \cap \{x_2, x_5\} = \{x_2, x_5\}$$
$$\delta(x_3) = \delta_a(x_3) \cap \delta_b(x_3) = \{x_2, x_5\} \cap \{x_1, x_3, x_4, x_6\} = \{\emptyset\}$$
$$\delta(x_4) = \delta_a(x_4) \cap \delta_b(x_4) = \{x_2, x_5\} \cap \{x_1, x_3, x_4, x_5\} = \{x_5\}$$
$$\delta(x_5) = \delta_a(x_5) \cap \delta_b(x_5) = \{x_2, x_5\} \cap \{x_2, x_4, x_5\} = \{x_2, x_5\}$$
$$\delta(x_6) = \delta_a(x_6) \cap \delta_b(x_6) = \{x_1, x_6\} \cap \{x_1, x_3, x_6\} = \{x_1, x_6\}$$

With the given neighborhood relations, the lower and upper approximations of X_1 and X_2 are given as

$$\underline{N}X_1 = \{x_1, x_6\} \; and \; \overline{N}X_1 = \{x_1, x_6\}$$
$$\underline{N}X_2 = \{x_2, x_5\} \; and \; \overline{N}X_2 = \{x_2, x_4, x_5\}$$

The following algorithm summarizes the proposed RNRS based feature selection method.

Algorithm2 – Forward Feature Selection based on Range specific NRS model.

Input: $\langle U, C \cup D, f\rangle$ *and* δ

Output: R → the reduct, contains selected attributes and their ranges

1. $R \leftarrow \emptyset$
2. For each $a_i \in C$
   a. Compute their ranges
3. **for** each $a_i \in C - R$
   a. Compute $\psi_{R \cup a_i}(D) = \frac{|POS_{B \cup a_i}(D)|}{|U|}$
   b. Compute $S(a_i, R, D) = \psi_{R \cup a}(D) - \psi_R(D)$
4. **end**
5. Select the attribute a_k satisfying $S(a_k, R, D) = \max_i(S(a_i, R, D))$
6. **if**$S(a_k, R, D) > \epsilon$, ϵ is the small positive number used to control the convergence
   a. $R \leftarrow R \cup a_k$
   b. goto Step-2
7. **else**
   a. return R
8. **endif**

V. EXPERIMENTAL SETUP

The performance of the proposed CG-SVM is studied with three different driving datasets such as (i) Ford's stay alert, (ii) Warwick-JLR Driver Monitoring Dataset (WJ-DMD), and (iii) National Tsing Hua University (NTHU) Driver Drowsiness Detection Dataset.

In Ford's stay alert driver's dataset, each sample is representing a sequential data, recorded at every 100ms during a driving session on the road. The sample consists of 100 participants of different age level, genders and ethnic backgrounds. There were 33 columns of data, collected from 610 drivers, and 1210 trials for each. In total the dataset has the dimension of 738100 samples with 33 measures, where the first two columns could be ignored as they maintain the sequential numbers, hence, the dataset dimension is reduced to 738100×31. The dataset is divided into two sets, 510 drivers' trials training and the rest of 100 drivers' trails for testing.

Taylor et al., (2013) collected the Warwick-JLR Driver Monitoring Dataset, there were two data streams inspected, namely the physiological and vehicle telemetry data streams.

The physiological data consisted of the ECG and Electrodermal Activity (EDA) signals, from which the Heart Rate (HR), Heart Rate Variability (HRV), Skin Conductance Level (SCL) and Electrodermal Response (EDR) frequency were extracted, and the vehicle telemetry data consists of eleven attributes such as cruise control, brake on, engine speed, engine torque, engine coolant temperature, gear selected, steering wheel movement speed, steering wheel angle, suspension height, throttle position and Yaw Rate. In all together the dataset has the dimension of 6 physiological and 11 vehicle telemetry data, 17 columns with 10000 samples of data.

National Tsing Hua University (NTHU) Driver Drowsiness Detection Dataset (Weng et al., 2016) dataset consists of 22 subjects (Figure 1) of various ethnicities. Under day and night illumination conditions, all of these subjects are recorded in a variety of simulated driving scenarios which includes conventional driving mode, yawning, slow blink rate, conscious laughter, and dizzy dozing. Consecutively, in the experiment made by an infrared (IR) illumination whose purpose was to acquire IR videos included in the dataset collection, the acquired videos resulted in a resolution of 640 X 480 in AVI format with the videos of scenarios being 30 frames per second. The videos used for testing are, however, produced by combining videos of different driving scenarios.

Figure 1. NTHU dataset including 22 subjects with different of ethnicities

The driver's inattention is recognized through facial regions extracted from a frontal cameral facing the driver, with these signals Action Units (AU) and gaze (head poses) features are extracted for classification. These feature vectors are labelled under two classes such as distracted and normal. The following text describes the feature extraction step for NTHU dataset, as discussed in Li &Busso (2013).

Facial Action Unit - The existing drivers' distraction detection system state that facial features are the most suitable feature to identify their inattention. The facial emotions are key while talking to someone or even for cognitive distractions too. In specific, the brow motion and eye lid movements are the key features for cognitive load. The description of facial expressions are defined in Facial Action Coding System (FACS) framework (Ekman, 1997). The facial AUs listed in this framework represent the muscle activity that produces various facial expressions. These information could be used to identify whether a person is behaving normal or in stress/pain.

Bartlett et al., (2006) constructed the Computer Expression Recognition Toolbox (CERT) for estimating facial features. With this toolbox, one can extract 20 AUs from frontal faces at every 10 sec interval and 8 statistical measures for each AU as given in Table 5. Altogether, a feature set of 160 values is constructed for each video.

Table 5. Visual Features for the Analysis

Low Level Features		
Action Units (AUs)		
Inner Brow Raiser (AU1)	Upper Lip Raiser (AU10)	Lip Tightener (AU23)
Outer Brow Raiser (AU2)	Lip Corner Puller (AU12)	Lip Pressor (AU24)
Brow Lowerer (AU4)	Dimpler (AU14)	Lips part (AU25)
Upper Lid Raiser (AU5)	Lip Corner Depressor (AU15)	Jaw Drop (AU26)
Cheek Raiser (AU6)	Chin Raiser (AU17)	Lip Suck (AU28)
Lid Tightener (AU7)	Lip Puckerer (AU18)	Blink (AU45)
Nose Wrinkler (AU9)	Lip Stretcher (AU20)	
Gaze Related Features		
Head Yaw (Yaw)	Head Pitch (Pitch)	Head Roll (Roll)
Statistical Features		
Mean	Minimum (Min)	Skewness
Standard Deviation	Range	Kurtosis
Maximum	Inner-Quartile Range (IQR)	
Global Features		
Longest Eyes-Off-Road (LEOR) Duration		
Eyes-Off-Road (EOR) Duration		

Gaze Related Features - Gaze feature like head pose provides most relevant information about driver's attention as discussed in Whitehill&Movellan (2008). The head pose features correspond to the 3D head orientations represented by yaw, pitch and roll angles. These three head pose angles along with eight statistics are estimated, in total there were 24 gaze features. In addition to AUs and gaze features, two off-the-road gaze features such as total eye-off-the-road (EOR) duration, and longest eye-off-the-road (LEOR) are estimated. EOR represents the time taken for secondary tasks and LEOR receives the time taken for each glance. The complete feature set has the dimension of 186, which includes 160 facial action units, and 26 gaze features, which are going to be further reduced with the proposed Range specific Neighborhood Rough Set (RNRS) approach.

Retrieval Number: D9780118419/2019©BEIESP
DOI:10.35940/ijrte.D9780.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

VI. RESULTS AND DISCUSSIONS

Table 6 presents the selected features with RNRS methods along their ranges for the Ford's stay alert dataset. The feature selection performance is compared with Neighborhood Rough Set (NRS) model (Hu et al., 2008) and Kernelized Fuzzy Rough Set (KFRS) model Du et al., (2018). Though the number of selected features is higher than the other methods, the classification performance is significantly improving with these feature ranges as shown in Table 12. Table 7 presents the range of the selected attributes.

Table 6. List of selected attributes from Ford's Stay Alert Dataset

Methods	# ReducedAttributes (#31)	List of Selected Attributes
RNRS	19	1, 2, 3, 4, 5, 7, 9, 12, 13, 14, 16, 17, 19, 21, 22, 23, 25, 29, 30
NRS	12	1, 2, 3, 4, 13, 14, 16, 17, 22, 23, 25, 29
KFRS	14	1, 2, 3, 4, 5, 9, 13, 14, 16, 17, 22, 23, 25, 29

Table 7. Selected Range for the Feature Subset from RNRS method with Ford's Stay Alert Dataset

Selected Attribute	Range	
	Lower Bound	Upper Bound
1	0.77	0.80
2	0.37	0.51
3	0.59	0.79
4	0.45	0.80
5	0.45	0.66
7	0.40	0.80
9	0.40	0.50
12	0.07	0.45
13	0.36	0.79
14	0.80	0.92
16	0.32	0.80
17	0.34	0.60
19	0.52	0.63
21	0.12	0.38
22	0.44	0.81
23	0.41	0.86
25	0.54	0.83
29	0.48	0.78
30	0.11	0.56

Table 8 and 9 presents the selected features with RNRS, NRS and KFRS methods from Warwick-JLR and the range of the selected attributes respectively.

Table 8. List of selected attributes from Warwick-JLR Dataset

Methods	# Reduced Attributes (#17)	List of Selected Attributes
RNRS	12	1, 2, 3, 5, 6, 7, 8, 11, 14, 15, 16, 17
NRS	10	1, 2, 3, 5, 6, 11, 14, 15, 16, 17
KFRS	11	1, 2, 3, 5, 6, 7, 8, 14, 15, 16, 17

Table 9. Selected Range for the Feature Subset from RNRS method with Warwick-JLRDataset

Selected Attribute	Range	
	Lower Bound	Upper Bound
1	0.24	0.69
2	0.16	0.84
3	0.43	0.86
5	0.04	0.68
6	0.14	0.33
7	0.51	0.94
8	0.60	0.85
11	0.00	0.96
14	0.13	0.83
15	0.27	0.72
16	0.24	0.77
17	0.18	0.82

Table 10 presents the selected features with RNRS, NRS and KFRS methods from NTHU dataset and their range of the selected attributes mostly lies between 0.18 and 0.85.

Table 10. List of selected attributes from NTHU Dataset

Methods	# Reduced Attributes (#186)	List of Selected Attributes
RNRS	82	2,8,9,11,13,14,15,16,18,20,21,22,25,26,27,29,32,33,34,35, 36,38,39,41,46,51,55,56,58,62,63,64,66,68,75,77,78,88,89, 91,93,98,100,101,103,107,116,117,118,119,122,123,125, 128,130,132,133,134,135,137,140,142,143,146,148,154,155,157,158,162,163,166,169,170,171,173,175,176,178,179, 181,185
NRS	70	2,8,9,11,13,14,18,20,21,22,25,26,27,29,32,33,34,35, 36,38,39,41,46,51,58,62,63,64,66,68,75,77,78,88,89, 91,93,98,100,101,118,119,122,123,125,128,130,132,133, 134,135,137,146,148,154,155,157,158,162,163,166,169, 170,171,173,175,176,178,179,181
KFRS	81	2,8,9,11,13,14,15,16,18,20,21,25,26,27,29,32,33,34,35,36, 38,39,41,46,51,55,56,58,62,63,64,66,68,75,77,78,88,89,91, 93,98,100,101,103,107,116,117,118,119,122,123,125,128, 130,132,133,134,135,137,140,142,143,146,148,154,155, 157,158,162,163,166,169,170,171,173,175,176,178,179, 181,185

The classification is performed with SVM classifier and the accuracy is reported for both the selected feature subsets. Table 11 reported the classification accuracy for all three datasets, for the proposed RNRS feature selection model, the samples within the range alone taken for training. The results indicate that the proposed RNRS model based feature selection outperforms other feature selection methods with greater classification accuracy.

Table 11. Classification Accuracy with selected features from Rough Set based Methods

Datasets	RNRS	NRS	KFRS
Ford's Stay Alert	0.9809	0.8934	0.8706
Warwick-JLR	0.9307	0.9307	0.9113
NTHU	0.8919	0.8181	0.8021

VII. CONCLUSIONS

A novel Range specific Neighborhood Rough Set (RNRS) model is proposed here for identifying relevant feature in the context of driver inattention detection problem. The proposed model not only identifies the relevant attributes, also estimate the appropriate range of them towards improving the classification accuracy. The performance of the proposed RNRS based feature selection method is studied with three different driver datasets: Ford's stay alert, Warwick-JLR and NTHU datasets. The quantified results indicate the superior performance of the proposed rough set model.

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