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Multi-Category Classification of Ground Vehicles Based on the Acoustic Data of Multiple-Terrains Using Fuzzy Logic Rule-Based Classifiers

by

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Abstract

This report summarizes our studies conducted from July 2003 to July 2004 for the multi-category classification of ground vehicles based on the acoustic data of multiple-terrains.

Data pre-processing (including elimination of redundant records, processing of data distortion, and generation of prototypes), feature extraction, and uncertainty analysis were performed before classifiers were designed.

We established the Bayesian classifier, and type-1 and interval type-2 fuzzy logic rule-based classifiers (FLRBC). These classifiers have similar architectures, consist of four subsystems each for one terrain, and have one probability model (Bayesian classifier) or one fuzzy logic rule (type-1 and interval type-2 FLRBCs) for each kind of vehicle on each terrain. They differ in the way that this common architecture is implemented.

Experiments were conducted to evaluate the performance of all classifiers. Experimental results revealed that 1) for the non-adaptive working mode, both the type-1 and interval type-2 FLRBCs have better performance (smaller mean and standard deviation of classification error rates) than the Bayesian classifier, and the interval type-2 FLRBC has better performance than the type-1 FLRBC; 2) each classifier has a smaller average but a slightly larger standard deviation of classification error rates in the adaptive working mode than in the non-adaptive mode; and 3) for the adaptive working mode, both the type-1 and interval type-2 FLRBCs have better performance than the Bayesian classifier, and the interval type-2 FLRBC has better performance than the type-1 FLRBC.

We applied all classifiers obtained from the above experiment to blind data records (provided to us by the Army Research Laboratory), and used spatio-temporal decision fusion techniques to obtain overall decisions from local decisions. For each blind data record, by

varying the number of classifier designs and the number of data blocks, we obtained different overall decisions.

With this report we have completed our study into the *classification of ground vehicles based on their acoustic emissions by using fuzzy logic rule based classifiers.* Our overall conclusion from this study is that FLRBCs always outperform a Bayesian classifier and look quite promising for real-time applications.

Chapter 1

Introduction

During the first two years of our study (July 2001 - July 2003), we have investigated the binary and multi-category classification of ground vehicles based on the acoustic data of the *normal* environmental conditions (i.e., terrain C) [4, 5]. We have extracted features from the raw acoustic data, analyzed feature uncertainties, designed the Bayesian and fuzzy logic rule-based classifiers (FLRBC), and conducted experiments to evaluate the performance of these classifiers. We have also applied our classifiers to the binary and multi-category classification of blind data records in the normal terrain. More specifically:

- We have observed that the acoustic emissions of ground vehicles contain a wealth of information, which can successfully be used for vehicle classification.
- We have observed that the features that are extracted from the acoustic measurements of ground vehicles are time-varying and contain a lot of uncertainties, because the acoustic emissions of a ground vehicle are subject to variations of the environmental conditions (e.g., terrain and wind) and vehicle-traveling speed, and the signal-to-noise ratio of the acoustic measurements are subject to the variation of the distance between

the vehicle and the sensor system.

- Since it is impossible to establish precise mathematical models to describe the variations and uncertainties of the features, we have proposed to use either probability density functions or fuzzy sets (type-1 and interval type-2 fuzzy sets) to model these variations and uncertainties.

- For three binary classification problems—tracked versus wheeled vehicles, heavy-tracked versus light-tracked vehicles, and heavy-wheeled versus light-wheeled vehicles, we have designed the Bayesian classifiers and FLRBCs. The Bayesian classifiers were established based on the assumption we made for the probability distribution of the features, and had each kind of vehicle associated with one multi-variate Gaussian probability density function. The FLRBCs were established based on the fuzzy set models we chose to describe the features, and had each kind of vehicle associated with one fuzzy logic rule. Each FLRBC was implemented in two forms — one based on type-1 fuzzy sets, and the other based on interval type-2 fuzzy sets. Through experiments we have observed that 1) in the leave-one-out experiments, both the type-1 and interval type-2 implementations of the FLRBCs have significantly smaller average and standard deviation of classification error rates than the Bayesian classifiers, and the type-1 and interval type-2 implementations of the FLRBCs have similar average and standard deviation although the interval type-2 implementations have slightly smaller average and standard deviation than the type-1 implementations; and, 2) in the leave-M-out experiments, both the type-1 and interval type-2 implementations of the FLRBCs have significantly smaller average and shorter confidence interval of classification error rates than the Bayesian classifiers, and the type-1 and interval type-2 implementations of the FLRBCs have similar average and confidence interval although the interval type-

2 implementations have slightly smaller average than the type-1 implementations for most of time.

- For the multi-category (heavy-tracked, light-tracked, heavy-wheeled and light-wheeled vehicles) classification problem, we have established 1) the Bayesian classifier, 2) the non-hierarchical FLRBC architecture, 3) the hierarchical FLRBC architecture in parallel, and 4) the hierarchical FLRBC architecture in series. Again, the Bayesian classifier was established based on the assumption we made for the probability distribution of the features, and had each kind of vehicle associated with one multi-variate Gaussian probability density function; and each FLRBC architecture was established based on the fuzzy set models we chose to describe the features, had each kind of vehicle associated with one fuzzy logic rule, and was implemented in two forms — one based on type-1 fuzzy sets, and the other based on interval type-2 fuzzy sets. Through experiments, we have observed that in all experiments (including the leave-one-out, leave-two-out, and 10-fold cross validation experiments) 1) both the type-1 and interval type-2 implementations of each FLRBC architecture have substantially smaller average and standard deviation (or confidence interval) of classification error rates than the Bayesian classifier, 2) for each FLRBC architecture, its interval type-2 implementation has smaller average than its type-1 implementation, although sometimes the interval type-2 implementation has slightly larger standard deviation (or longer confidence interval) than the type-1 implementation, and 3) the interval type-2 implementations of the non-hierarchical and hierarchical in series architectures always have the smallest average and relatively smaller standard deviation. However, through a computational complexity analyses, we have found that the non-hierarchical architecture is computationally much less complex than is the hierarchical in series architecture.

- We have observed that each classifier can achieve even better performance when a majority voting technique is used during the adaptive working mode (in which decisions are made based on all available data).

- We have applied the interval type-2 FLRBC designed for the binary classification of tracked versus wheeled vehicles to the 51 blind data records of the normal terrain, and have had 47 and 49 data records correctly classified in the worst and best cases, respectively.

- We have also applied the Bayesian classifier and the interval type-2 implementations of the three FLRBC architectures designed for the multi-category classification of heavy-tracked, light-tracked, heavy-wheeled and light-wheeled vehicles to the 51 blind data records of the normal terrain, and have had 51% and 76% classification accuracy rates for the Bayesian classifier, and 78% and 92% classification accuracy rates for the FLR-BCs, in the worst and best cases, respectively.

In the third year of our study (July 2003 - July 2004), we have conducted research on the multi-category classification of ground vehicles based on the acoustic data of *all* environmental conditions, namely, the desert (terrain A), arctic (terrains B and D), and normal (terrain C) environments. We were constrained by our sponsors to design one classifier that could operate in all four terrains without a priori knowledge of a specific terrain.

This reports summarizes our study of the third year, and is organized as follows. Chapter 2 discusses data pre-processing, feature extraction and uncertainty analysis. In Chapters 3 and 4 we describe the designs for the Bayesian and fuzzy logic rule based classifiers. Chapter 5 provides the experimental and blind results. Finally, in Chapter 6, we draw conclusions.

Chapter 2

Data Pre-Processing, Feature Extraction and Uncertainty Analysis

In this chapter we focus on data pre-processing, feature extraction and uncertainty analysis. In this part of our work we not only converted the raw data (acoustic measurements) into feature vectors (based on which classification is performed), but also developed an understanding of the distribution and uncertainties of feature vectors of different kinds of vehicles in different environmental conditions. Our starting hypothesis was that features will be more uncertain across all four terrains than they are across just the normal terrain, and an interval type-2 FLRBC, which can model such uncertainties, should therefore perform even better than it did for just the normal terrain.

2.1 Data Pre-Processing

Run and Record: Our research has been based on the Acoustic-Seismic Classification /Identification Data Set (ACIDS) that consists of 274 files of acoustic measurements collected by two sensor systems for nine kinds of ground vehicles in four environmental conditions.

We still distinguish between the *run* and *record*. Each run corresponds to a ground vehicle traveling at a constant speed toward the sensor system, passing the closest point of approach (CPA), and then moving away from the sensor system. Associated with each run, there may be two records if the two sensor systems were both operating to collect the acoustic data, or one record if only one sensor system was operating. The number of runs and records for each kind of vehicle in each environmental condition is summarized in Table 2.1. We have observed that:

- On Terrain A (desert) there are runs for only six kinds of vehicles, and no runs for the *light-tracked* category.
- On Terrain B (arctic) there are runs for only five kinds of vehicles, and no runs for the *light-tracked* category.
- On Terrain C (normal) there are runs for all nine kinds of vehicles .
- On Terrain D (arctic) there are runs for only six kinds of vehicles, but there are runs for all four categories of vehicles.

Distortion Processing: In each record, the magnitude of the data is expected to be low and flat in the beginning (which corresponds to the vehicle being far away before reaching the CPA), to increase to the highest value and then decrease in the middle part (which corresponds to the vehicle moving toward, reaching and then moving away from the CPA), and to be low and flat in the end (which corresponds to the vehicle being far away after reaching the CPA), as shown in Fig. 2.1. However, we have observed in some records the following exceptions.

- There is noise with huge magnitude in the beginning or the end part of a record whose magnitude is even higher than the magnitude of measurements around the CPA, as shown in Fig. 2.2.

- The magnitude of measurements exceeds the legitimate range of the sensor system so that there are saturated measurements, as shown in Fig. 2.3.

- The record contains multiple modes, each of which has a pattern similar to Fig. 2.1 and corresponds to the magnitude of the data first increasing, then reaching the CPA and finally decreasing, as if the sensor system had collected multiple runs into one record, as shown in Fig. 2.4.

Occasionally there are two records associated with the same run, for which we have chosen the record with less distortion (e.g., less saturation). In the rest of this report, we use *run* and *record* interchangeably. We have taken the following measures for each run to overcome the distortion:

- Because noise with large magnitude usually occurs in the beginning or the end of a run, we have restrained the time interval in which to search for the CPA not be at either end of an acoustic record. Doing so can eliminate the effect of such noise.

- For the runs in which the magnitude of measurements exceeds the legitimate range of the sensor system, we have simply discarded the saturated measurements (i.e., the framed part in Fig. 2.3) and concatenated the measurements before and after the discarded part. Doing so may introduce high frequency components, but only into one or two blocks.

- For the abnormal runs in which there exists multiple modes, we have manually located the time interval that looks the most reasonable (i.e., the framed part in Fig. 2.4) and then searched for the CPA.

CPA-based Prototype Generation: A complete run lasts from tens to hundreds of seconds. At the sampling rate of 1025.641 Hz, there are a huge number of measurements in each run. Additionally, these measurements are non-stationary because their signal to noise ratio (SNR) varies within the run. These two factors make it impractical to process all measurements of a run simultaneously; hence, we have segmented them into one-second blocks, and treated one block (rather than a whole run) as one prototype.

For each run we have considered the time (t_0) that the acoustic measurement has the maximum magnitude to be the time that the traveling vehicle reaches the CPA. We have then generated 80 data blocks by sliding a 1024-point rectangular window (about one second) with 50% of window overlap to the left and right of t_0.

As discussed earlier, for those abnormal runs in which the magnitude of measurements exceeds the legitimate range of the sensor system, we have discarded saturated measurements and concatenated the measurements before and after the discarded part. Doing so may introduce high frequency components. However, because the adjacent blocks have 50% of window overlap, the concatenated measurements only appear in up to two adjacent blocks. This means that the impact of concatenation is limited.

2.2 Feature Extraction

During the previous two years, we focused on the acoustic data of the normal environmental conditions (Terrain C). We assumed that the fundamental frequency f_0 of all kinds of vehicles in this normal environmental condition is in the range $[9, 18]$ Hz, and applied the harmonic line association (HLA) algorithm (whose complete description is provided in [4, 5]) to extract the magnitudes of the 2nd through 12-th harmonic components as the features.

Because we do not have any a priori knowledge about the distribution of the fundamental frequency of all kinds of vehicles in all four environmental conditions, we have used the interval $[8, 20]$ Hz (which was proposed by Wellman et. al. in [3]) as the initial range of f_0, and have then used the HLA algorithm to extract feature vectors for all data blocks.

After feature extraction, each data block is completely characterized by its 11-dimensional feature vector; hence, in the rest of this report, we use *data block* and *feature vector* interchangeably.

2.3 Uncertainty Analysis

Although the traveling speed of a ground vehicle is approximately constant within each run, it varies from run to run, ranging from 5 km/hr to 40 km/hr. The variation of the traveling speed, along with the environmental variations (e.g., wind and terrain), makes the acoustic emissions of the same kind of vehicle different from run to run. Within each run, when the vehicle is far away from the sensor system (in the beginning and ending parts of a run), the acoustic measurements mainly consist of background noise, whereas when the vehicle is closer to the sensor system (in the middle part of a run), the acoustic measurements consist of acoustic emissions of the ground vehicle as well as the background noise. The variation of the distance between the traveling vehicle and the sensor system makes the SNR of the measurements variable within each run. The above two sources of variations are both embodied in the uncertainties of the features that are extracted from the acoustic measurements.

Because the principal component analysis (PCA) provides a tool to visualize high dimensional data in a two- or three-dimensional plane [1], we have performed the PCA for the feature vectors of terrains A, B and D [1], and have represented each feature vector by using

[1]Since the computational effort of PCA would be very high for a large number of data, we have not

its two most prominant principal components. More specifically, given the feature vectors of all data blocks of one terrain, we have performed preprocessing (by using the function *prestd* provided in Matlab) so that the processed feature vectors have zero mean and unit standard deviation in each dimension, and we have then performed the PCA analysis (by using the function *prepca* provided in Matlab) to the above processed feature vectors. Figs. 2.5-2.7 show the two most prominant principal components of the feature vectors on terrain A, B, and D respectively . Observe from these figures that:

- In Fig. 2.5 a, the heavy-tracked data (red) overlap with the HW-b (blue) and the LW-b (black) data , which demonstrates the difficulty of distinguishing *heavy-tracked* vehicles from the *heavy-wheeled* and *light-wheeled* vehicles on terrain A.

- In Fig. 2.6 a, the heavy-tracked (red), HW-b (blue) and LW-a (black) data have much overlap, which which demonstrates the difficulty of distinguishing among the *heavy-tracked*, *light-tracked* and *heavy-wheeled* vehicles on terrain B.

- In Fig. 2.7 a, the heavy-tracked (red), LT-a (magenta) and HW-b (blue) data have much overlap, which demonstrates the difficulty of distinguishing among the *heavy-tracked*, *light-tracked* and *heavy-wheeled* vehicles on terrain D.

For each *run*, by using the feature vectors of the 80 CPA-based data blocks, we have first computed the mean (*run-mean*) and standard deviation (*run-standard deviation*) in each feature dimension. We have then represented the feature distribution in the i-th ($i = 1, \ldots, 11$) dimension by using the interval

$$[(\text{run-mean})_i - 2\,(\text{run-standard deviation})_i\,, (\text{run-mean})_i + 2\,(\text{run-standard deviation})_i].$$

performed the PCA for terrain C in which there are 7,120 feature vectors (80 feature vectors per run × 89 runs).

In this way, each *run* is represented by 11 intervals, one for each feature dimension, and these intervals are the ranges into which the feature vectors of one *run* fall with high probability.

Based on the feature ranges of individual runs, we have been able to determine the ranges into which the feature vectors of each *kind* of vehicle fall with high probability, i.e., to represent each *kind* of vehicle by using intervals, too. More specifically, given the terrain T_r ($r = 1, 2, 3, 4$), then the feature distribution of the vehicle V_j in the i-th dimension is represented by using an interval $\left[(\text{left point})_{i,j}, (\text{right point})_{i,j}\right]$ that contains all runs of V_j, i.e.,

$$\begin{aligned}(\text{left point})_{i,j} &= \min_{\text{run}_k \in V_j} \left[(\text{run-mean})_{i,k} - 2\,(\text{run-standard deviation})_{i,k}\right] \\ (\text{right point})_{i,j} &= \max_{\text{run}_k \in V_j} \left[(\text{run-mean})_{i,k} + 2\,(\text{run-standard deviation})_{i,k}\right]\end{aligned}$$

In the above two equations, $j \in \{1, 2, \ldots, M_r\}$ is the index of the vehicle (so that V_j represents the j-th kind of vehicle), M_r is the number of different kinds of vehicles on terrain T_r, $i \in \{1, 2, \ldots, 11\}$ is the index of the feature dimension, and k is the index of the run (so that run-mean$_{i,k}$ and run-standard deviation$_{i,k}$ represent the statistics of the i-th feature for the k-th run).

Figs. 2.8-2.11 show the feature ranges of all kinds of vehicles on all four terrains. Observe from these figures that for each kind of vehicle 1) the feature ranges on different terrains are different; and, 2) upon merger of feature ranges on different terrains, the merged range is larger than the range on the normal terrain in most of the feature dimensions (e.g., compare the black lines for terrain C and the lines of other colors for terrains A, B and D in Figs. 2.8-2.11). This demonstrates that the acoustic features across multiple terrains are more uncertain than the acoustic features across the normal terrain.

For each kind of vehicle on each terrain, based on the run-means and run-standard deviations of all its runs, we have computed the mean and standard deviation of run-means, and the mean and standard deviation of run-standard deviations. In the following, the mean of run-means is denoted as M-RM, the standard deviation of run-means is denoted as SD-RM, the mean of run-standard deviations is denoted as M-RSD, and the standard deviation of run-standard deviations is denoted as SD-RSD. For illustration purposes, we summarize these four statistics for the HT-a and HW-b vehicles on all four terrains in Tables 2.2-2.3. Observe from these tables that:

- For each kind of vehicle on each terrain SD-RM is not negligible compared to M-RM.
- For each kind of vehicle on each terrain, SD-RSD is not negligible compared to M-RSD.
- For each kind of vehicle on each terrain, SD-RM and SD-RSD are of similar magnitude.
- In some feature dimensions, the difference among the statistics for the same kind of vehicle on different terrains is not negligible when compared to the difference among the statistics of the different kinds of vehicles on the same terrain (e.g., in the fourth feature dimension, the M-RM difference of the HT-a vehicle between terrains A and B, $|1.1977 - 4.6728|$, is even greater than the M-RM difference between the HT-a and HW-b vehicles on terrain A, $|1.1977 - 1.4920|$).

Based on the above uncertainty analysis, we have drawn the following preliminary conclusions regarding the fuzzy set models for the acoustic features:

- Fuzzy set models should be appropriately chosen to account for the simultaneous variations in both the run-means and run-standard-deviations.
- Even for the same kind of vehicle, different fuzzy set models should be established for different terrains.

Table 2.1: The number of runs and records for each kind of vehicle in each environmental condition.

		Terrain A (desert)		Terrain B (arctic)		Terrain C (normal)		Terrain D (arctic)	
		runs	records	runs	records	runs	records	runs	records
Sub-total	**Heavy-Tracked**	29	40	22	36	46	63	16	16
	a (Vehicle 1)	12	17	12	18	15	22	5	5
	b (Vehicle 2)	9	13	6	12	8	12	0	0
	c (Vehicle 8)	4	6	4	6	15	17	6	6
	d (Vehicle 9)	4	4	0	0	8	12	5	5
Sub-total	**Light-Tracked**	0	0	0	0	15	15	6	12
	a (Vehicle 4)	0	0	0	0	15	15	6	12
Sub-total	**Heavy-Wheeled**	10	18	4	4	16	21	5	5
	a (Vehicle 3)	0	0	0	0	8	9	0	0
	b (Vehicle 5)	10	18	4	4	8	12	5	5
Sub-total	**Light-Wheeled**	3	3	1	1	12	16	12	24
	a (Vehicle 6)	0	0	1	1	8	12	12	24
	b (Vehicle 7)	3	3	0	0	4	4	0	0
Total		42	61	27	41	89	115	39	57

Table 2.2: The four statistics, M-RM, SD-RM, M-RSD, and SD-RSD, for the HT-a vehicle on all four terrains, where x_i ($i = 1, \ldots, 11$) represents the i-th feature dimension.

	Terrain A				**Terrain B**			
Feature	M-RM	SD-RM	M-RSD	SD-RSD	M-RM	SD-RM	M-RSD	SD-RSD
x_1	0.4596	0.3525	0.3074	0.2315	0.8227	0.4571	0.6140	0.3735
x_2	0.6484	0.3860	0.4633	0.2509	1.1608	0.4288	0.8363	0.2012
x_3	1.2313	0.7350	0.7687	0.4193	1.0655	0.4769	0.6439	0.3293
x_4	*1.1977*	0.6874	0.9714	0.7204	*4.6728*	2.0270	2.7308	1.3615
x_5	3.3590	1.6681	1.7966	0.7848	2.2185	0.8433	1.6284	0.8381
x_6	1.9463	1.3811	1.2074	0.3855	5.2506	1.1451	2.4879	0.2733
x_7	4.8849	2.6620	2.4363	1.2983	1.5879	0.3212	1.0115	0.5579
x_8	3.8127	3.8925	1.7547	1.2695	10.1616	3.0117	4.0106	0.8524
x_9	3.4541	1.4986	2.0178	0.7481	1.4360	0.4324	1.0775	0.4307
x_{10}	0.9803	0.2346	0.5534	0.1975	1.0267	0.3511	0.9639	0.5242
x_{11}	1.5625	0.4643	1.4753	0.9866	1.4945	0.4320	1.3259	0.7180

	Terrain C				**Terrain D**			
Feature	M-RM	SD-RM	M-RSD	SD-RSD	M-RM	SD-RM	M-RSD	SD-RSD
x_1	0.5591	0.1798	0.4285	0.1744	0.4149	0.0512	0.4071	0.1910
x_2	0.9035	0.4545	0.7120	0.5897	0.8477	0.1681	0.9064	0.6315
x_3	1.1057	0.4282	0.7727	0.4349	0.8235	0.4471	0.8503	0.5722
x_4	2.5829	1.4842	1.5826	0.7775	3.4249	1.9347	1.8071	0.8290
x_5	2.4094	1.3014	1.4380	0.5794	2.5579	0.5235	1.5221	0.5115
x_6	3.7644	2.1563	1.6170	0.7250	3.2274	0.5682	1.7286	0.6582
x_7	3.6858	3.2705	1.8474	1.5440	1.8585	0.2283	1.5073	1.1948
x_8	6.6479	4.0751	2.3849	0.8173	8.5936	1.5448	2.9030	1.0256
x_9	3.1014	2.6539	1.6051	1.3238	2.3680	0.4208	1.6325	1.0841
x_{10}	1.0076	0.2238	0.6311	0.2448	1.6078	0.4855	0.7180	0.2424
x_{11}	2.2443	1.2677	1.8725	1.5696	4.7150	2.8658	2.0747	1.3936

Table 2.3: The four statistics, M-RM, SD-RM, M-RSD, and SD-RSD, for the HW-b vehicle on all four terrains, where x_i $(i = 1, \ldots, 11)$ represents the i-th feature dimension.

	Terrain A				**Terrain B**			
Feature	M-RM	SD-RM	M-RSD	SD-RSD	M-RM	SD-RM	M-RSD	SD-RSD
x_1	0.3252	0.1970	0.3137	0.1876	0.9745	0.4637	0.4271	0.2462
x_2	1.4308	1.1881	0.8990	0.6238	3.5655	0.8558	1.3695	0.8670
x_3	1.6315	1.6887	2.0717	2.2048	1.4500	0.4042	1.9204	2.0760
x_4	**1.4920**	0.7165	1.4835	0.8033	3.8473	1.2424	1.6744	0.9077
x_5	13.9004	2.9741	4.0563	2.6924	12.2548	2.8507	4.5813	2.8937
x_6	1.0091	0.4630	1.4218	0.8930	1.1199	0.2031	1.3420	0.9025
x_7	1.3154	1.0969	1.8616	1.9146	1.9111	0.2236	2.4867	2.1072
x_8	2.1493	0.6356	2.6135	1.2404	1.0524	0.2376	2.2901	1.1327
x_9	0.7203	0.5213	1.0073	0.8613	2.7496	1.9524	1.9874	2.3086
x_{10}	0.7466	0.2524	0.7127	0.4508	0.5718	0.2286	0.6676	0.4943
x_{11}	1.5991	0.7420	1.4305	1.0200	0.6815	0.2466	1.2138	1.1064
	Terrain C				**Terrain D**			
Feature	M-RM	SD-RM	M-RSD	SD-RSD	M-RM	SD-RM	M-RSD	SD-RSD
x_1	0.4161	0.0966	0.3134	0.1705	0.2969	0.1036	0.2859	0.1735
x_2	4.8912	2.0042	1.5147	0.6389	1.2057	1.1880	1.0797	0.6436
x_3	1.0972	0.4369	0.6019	0.3307	0.4593	0.1739	0.6320	0.4483
x_4	2.8823	1.2893	1.5824	0.7031	1.0158	0.1905	1.3287	0.7708
x_5	14.6132	3.8612	2.8179	1.6325	17.2600	0.7594	3.0512	1.7808
x_6	1.4411	0.4766	1.3733	0.8047	0.8184	0.3433	1.2282	0.9267
x_7	0.5275	0.1547	0.5692	0.4413	0.7631	0.3142	1.0807	1.1876
x_8	2.6375	1.3749	2.2851	0.9437	1.7034	0.5568	2.3748	0.7883
x_9	0.5403	0.0953	0.7670	0.6578	0.6144	0.2279	1.3346	0.9000
x_{10}	0.8673	0.5767	0.6939	0.3981	0.6650	0.1793	0.6472	0.3553
x_{11}	1.2672	0.7683	1.0896	0.7426	1.3794	0.2497	0.9750	0.5209

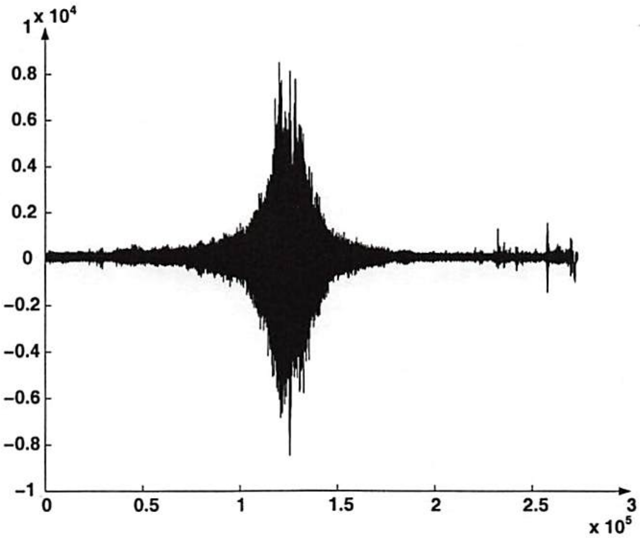


Figure 2.1: The first channel of a normal record of acoustic data.

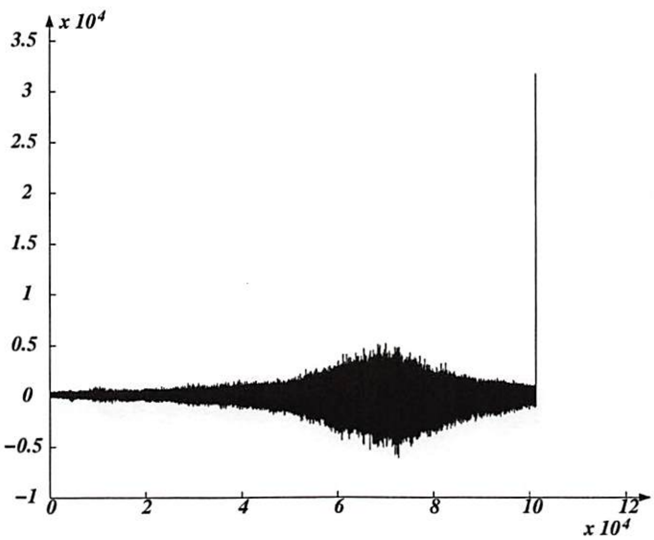


Figure 2.2: The first channel of an abnormal record of acoustic measurements in which there is big noise in the end.

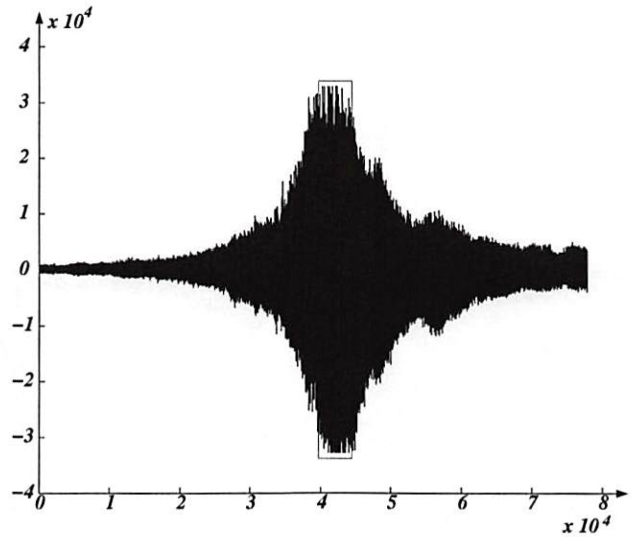


Figure 2.3: The first channel of an abnormal record of acoustic measurements in which the measurements in the frame exceed the legitimate range of the sensor system.

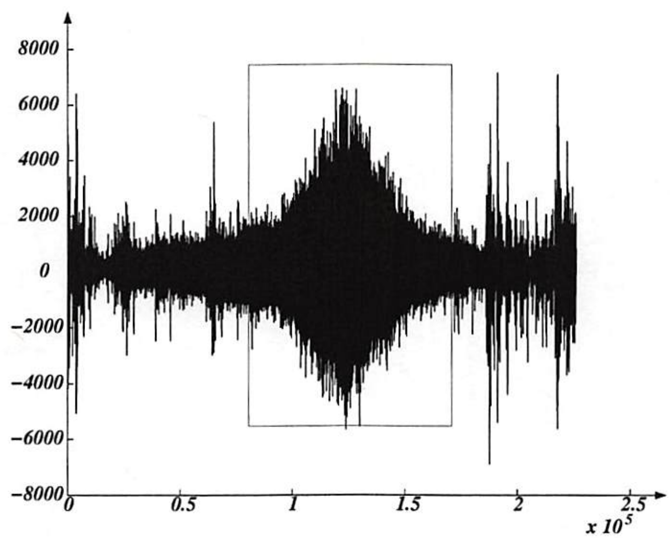


Figure 2.4: The first channel of an abnormal record of acoustic measurements in which only the framed part corresponds to the traveling (run) of the vehicle.

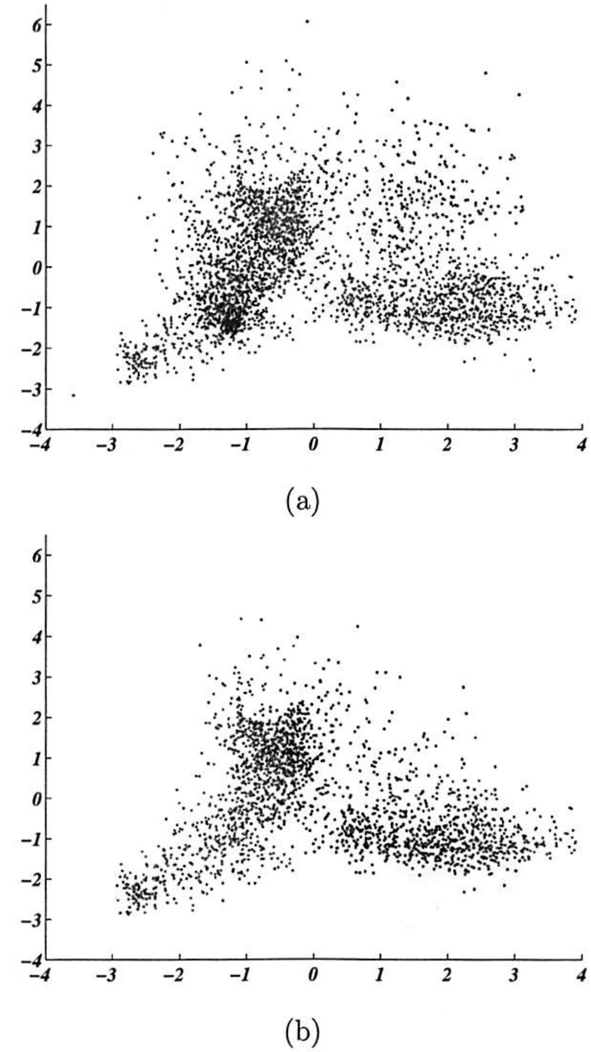
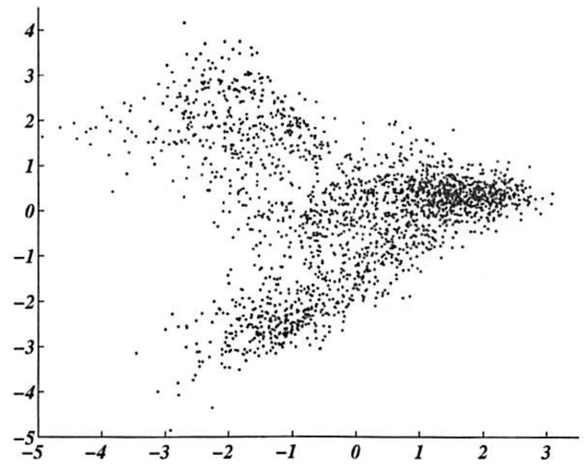
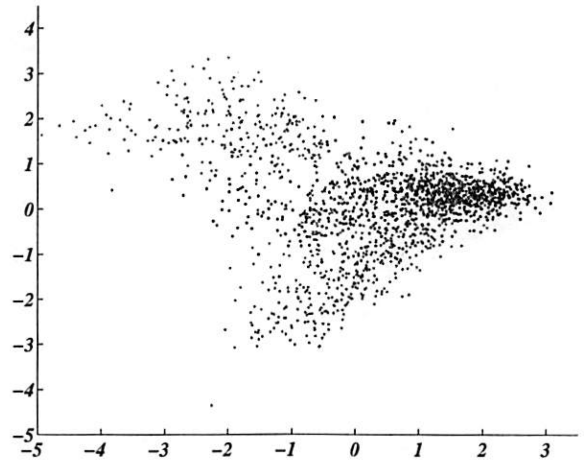


Figure 2.5: The two most prominant principal components of the feature vectors on terrain A, where each dot corresponds to one data block: (a) HT-a, b, c, d (red), HW-b (blue) and LW-b (black) vehicles, and (b) all four kinds of *heavy-tracked* vehicles: HT-a (black), HT-b (red), HT-c (blue) and HT-d (magenta). Note that there are no data for *light-tracked* vehicles on terrain A.

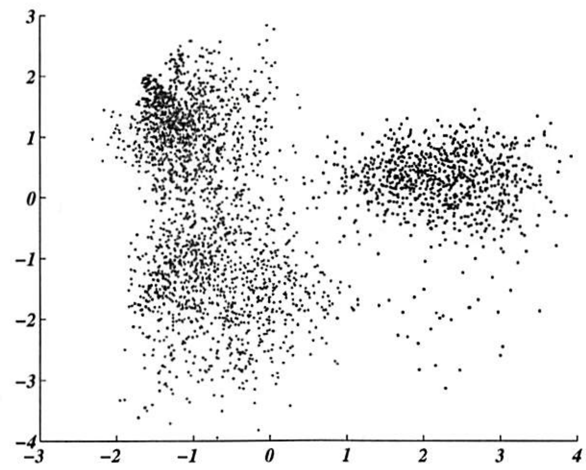


(a)

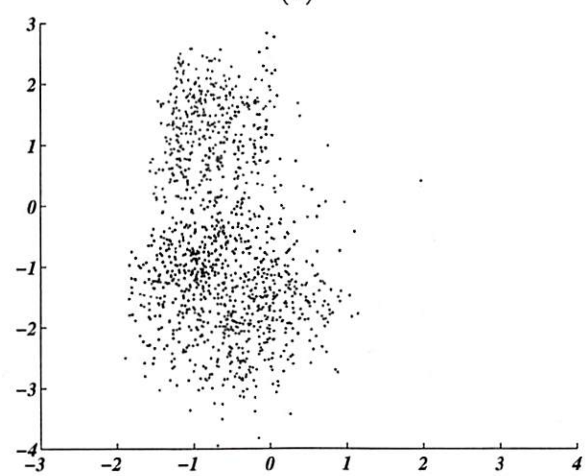


(b)

Figure 2.6: The two most prominant principal components of the feature vectors on terrain B, where each dot corresponds to one data block: (a) HT-a, b, c (red), HW-b (blue) and LW-a (black), and (b) all three kinds of *heavy-tracked* vehicles: HT-a (black), HT-b (red), and HT-c (magenta). Note that there are no data for *light-tracked* vehicles on terrain B.



(a)



(b)

Figure 2.7: The two most prominant principal components of the feature vectors on terrain D, where each dot corresponds to one data block: (a) HT-a, c, d (red), LT-a (magenta), HW-b (blue), and LW-a (black), and (b) all three kinds of *heavy-tracked* vehicles: HT-a (red), HT-c (blue), and HT-d (magenta).

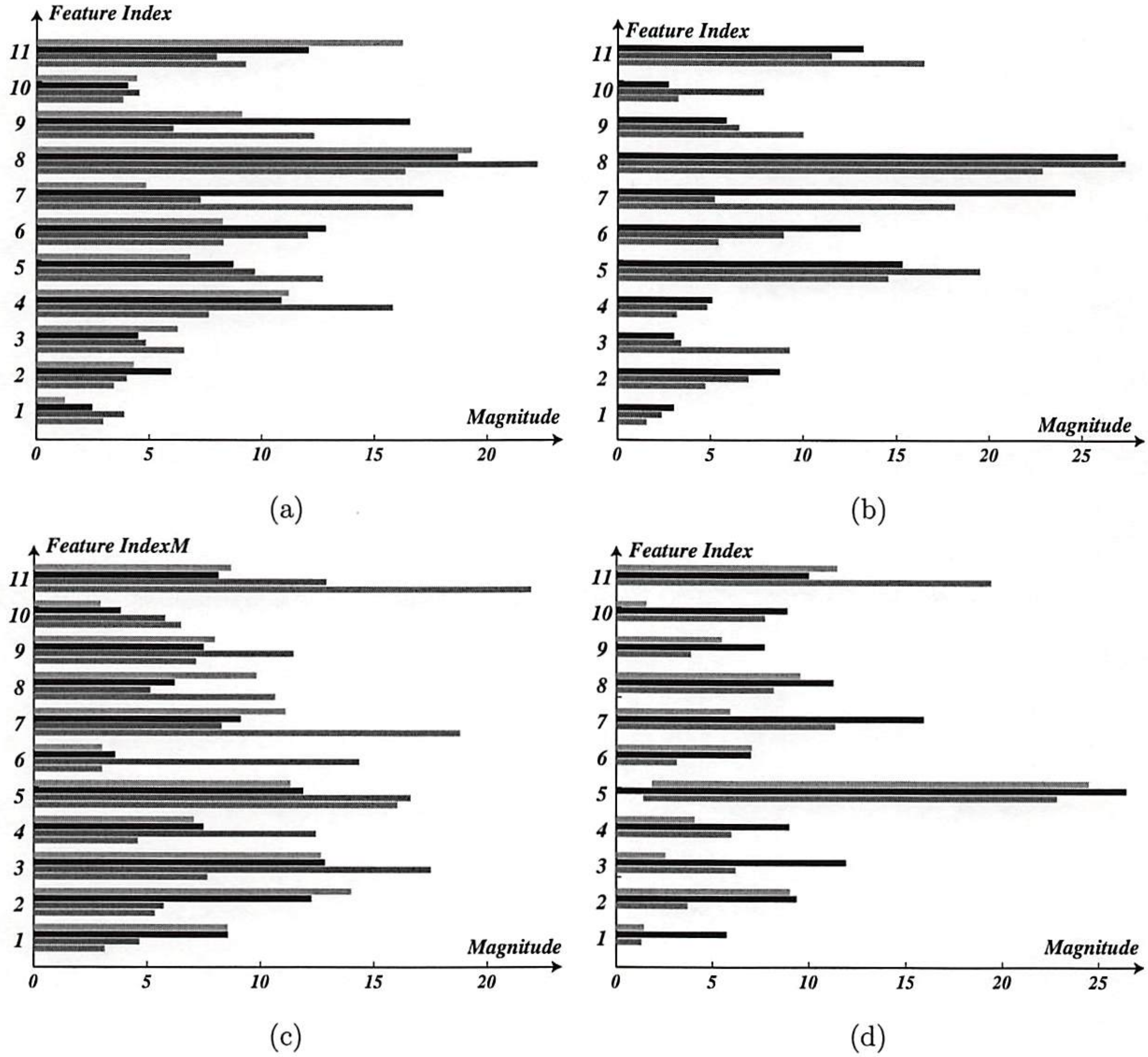


Figure 2.8: Range of features for heavy-tracked vehicles: (a) HT-a vehicle, (b) HT-b vehicle, (c) HT-c vehicle and (d) HT-d vehicle. In the figures, for each dimension, from bottom to top, the red lines are for the data of terrain A, blue lines are for the data of terrain B, black lines are for the data of terrain C, and magenta lines are for the data of terrain D.

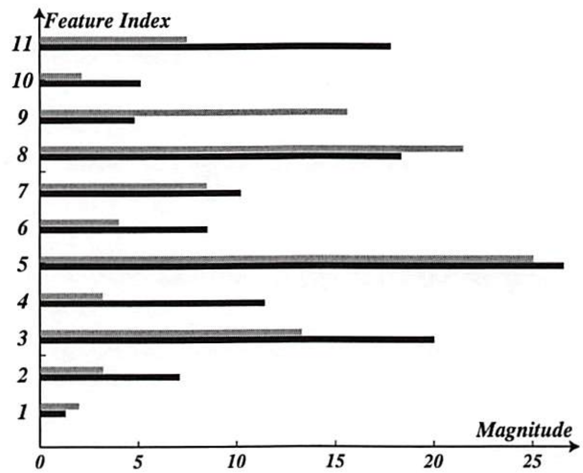
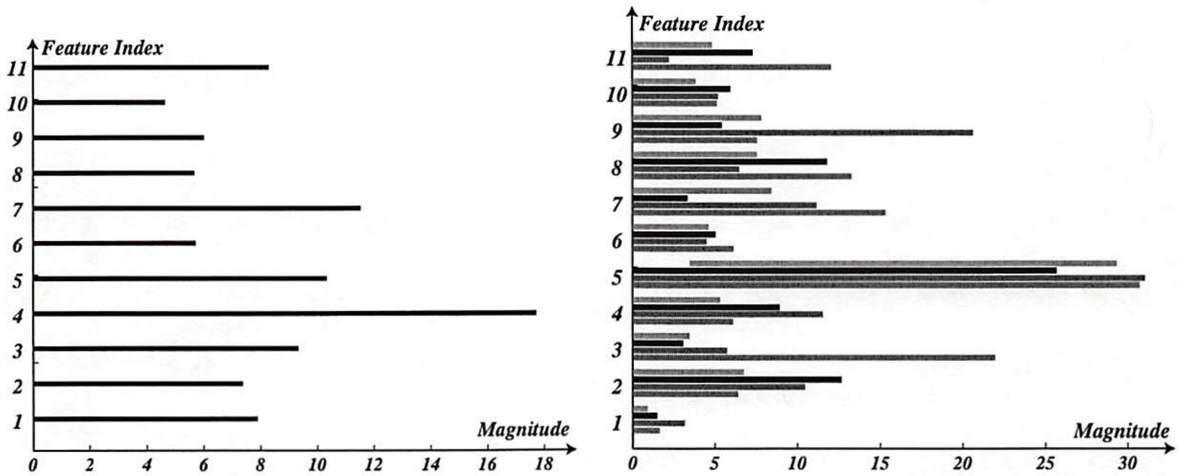


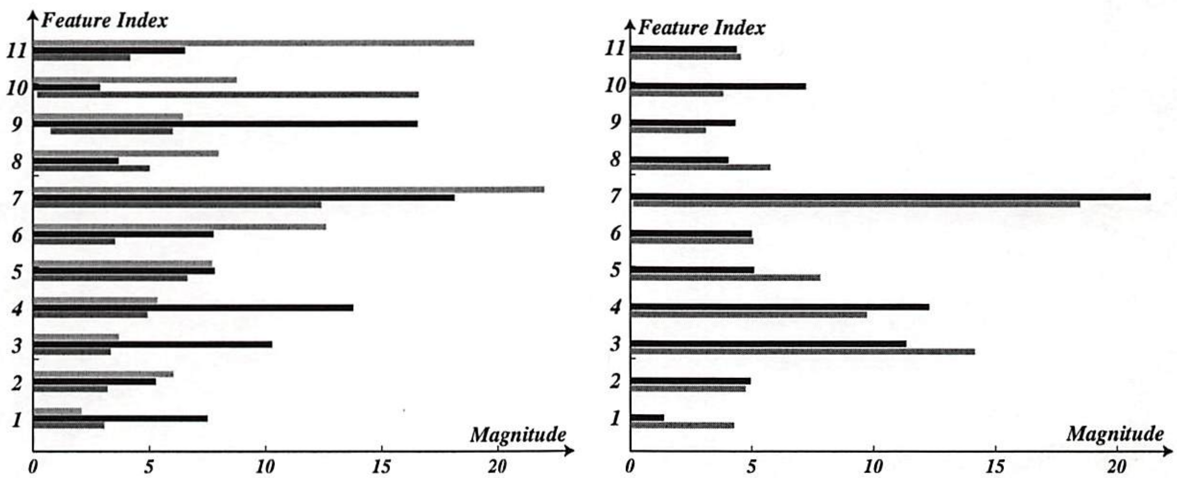
Figure 2.9: Range of features for the light-tracked vehicles. In the figure, for each dimension, from bottom to top, the black lines are for the data of terrain C, and magenta lines are for the data of terrain D.



(a)

(b)

Figure 2.10: Range of features for heavy-wheeled vehicles: (a) HW-a vehicle and (b) HW-b vehicle. In the figures, for each dimension, from bottom to top, the red lines are for the data of terrain A, blue lines are for the data of terrain B, black lines are for the data of terrain C, and magenta lines are for the data of terrain D.



(a) (b)

Figure 2.11: Range of features for light-wheeled vehicles: (a) LW-a vehicle and (b) LW-b vehicle. In the figures, for each dimension, from bottom to top, the red lines are for the data of terrain A, blue lines are for the data of terrain B, black lines are for the data of terrain C, and magenta lines are for the data of terrain D.

Chapter 3

Classifier Designs: Bayesian Classifier

The focus of our research is to apply fuzzy set, fuzzy logic and fuzzy logic system theories to the uncertainty estimation, modeling and processing for the multi-category classification of ground vehicles based on the acoustic data of multiple terrain conditions. To evaluate the fuzzy logic rule-based classifiers (FLRBC) in a fair way, we have also constructed the Bayesian classifier based on the assumptions we have made about the probability distribution of the acoustic features. So, in this chapter, we concentrate on the the design and implementation of the Bayesian classifier.

Fig. 3.1 depicts a generic classifier architecture for the multiple terrain classification of ground vehicles based on the acoustic data of multiple terrains, which can be implemented as either a Bayesian classifier or a FLRBC. In the rest of this chapter, we discuss the four sub-systems and decision fusion unit for the Bayesian classifier.

3.1 Sub-systems

The Bayesian classifier has four sub-systems, T_r ($r = 1, \ldots, 4$), each of which is responsible for the multi-category classification of ground vehicles in one terrain. Given an input feature vector $\mathbf{x}$, the local posterior probability of the category C ($\in$ {heavy-tracked, light-tracked, heavy-wheeled, light-wheeled}) associated with sub-system T_r, $P(C|\mathbf{x}, T_r)$, is computed as:

$$P(C|\mathbf{x}, T_r) = \frac{p(\mathbf{x}|C, T_r)P(C|T_r)}{p(\mathbf{x}|T_r)} = \frac{p(\mathbf{x}|C, T_r)P(C|T_r)}{\sum_C p(\mathbf{x}|C, T_r)P(C|T_r)} \tag{3.1.1}$$

where $P(\cdot)$ denotes a probability mass function (pmf), and $p(\cdot)$ denotes a probability density function (pdf). More specifically, $p(\mathbf{x}|C, T_r)$ is the conditional pdf of the feature vector $\mathbf{x}$ given the information of the category C and terrain T_r, and $P(C|T_r)$ is the conditional pmf of the category C given the information of the terrain T_r.

Because each *category* includes different *kinds* of vehicles (e.g., the heavy-tracked category includes HT-a, HT-b, HT-c and HT-d vehicles), the product $p(\mathbf{x}|C, T_r)P(C|T_r)$ can be re-expressed as:

$$p(\mathbf{x}|C, T_r)P(C|T_r) = p\left(\mathbf{x}, C|T_r\right) = \sum_{V_j \in C} p(\mathbf{x}, V_j|T_r) = \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r) \tag{3.1.2}$$

where V_j represents one kind of vehicle, $p(\mathbf{x}|V_j, T_r)$ is the conditional pdf of the feature vector $\mathbf{x}$ given the information of the vehicle kind V_j and terrain T_r, and $P(V_j|T_r)$ is the conditional pmf of the vehicle kind V_j given the information of the terrain T_r. Upon substitution of (3.1.2) into (3.1.1), $P(C, |\mathbf{x}, T_r)$ can be re-written as:

$$P(C|\mathbf{x}, T_r) = \frac{\sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)}{\sum_C \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)} \tag{3.1.3}$$

We assume that the conditional pdf of the feature $\mathbf{x}$ given the information of the vehicle kind V_j and terrain T_r, $p(\mathbf{x}|V_j, T_r)$, is described by a multi-variate Gaussian pdf as:

$$p(\mathbf{x}|V_j, T_r) \sim \aleph\left(\mathbf{x}; \mathbf{m}_{j,r}, \Sigma_{j,r}\right) \tag{3.1.4}$$

where $\mathbf{m}_{j,r}$ and $\Sigma_{j,r}$ are the mean vector and covariance matrix associated with V_j in terrain T_r. During the experiment, $\mathbf{m}_{j,r}$ and $\Sigma_{j,r}$ are estimated by using the training data of V_j in T_r as:

$$\mathbf{m}_{j,r} = \frac{1}{N_{j,r}} \sum_{\mathbf{x} \in V_j \text{ in } T_r} \mathbf{x} \tag{3.1.5}$$

$$\Sigma_{j,r} = \frac{1}{N_{j,r} - 1} \sum_{\mathbf{x} \in V_j \text{ in } T_r} (\mathbf{x} - \mathbf{m}_{j,r})(\mathbf{x} - \mathbf{m}_{j,r})^t \tag{3.1.6}$$

where $N_{j,r}$ is the number of training data of V_j in T_r. We also assume that the conditional pmf of the vehicle kind V_j given the information of the terrain T_r, $P(V_j|T_r)$, is uniform among all kinds of vehicles in that terrain. For example, only six kinds of vehicles have their acoustic emission data available on terrain A (see Table 2.1, hence, their conditional pmf given terrain A are all equal to 1/6. The conditional pmf of each kind of vehicle given each terrain is summarized in Table 3.1.

3.2 Decision Fusion

Given an input feature vector $\mathbf{x}$, each sub-system computes the local posterior probability of each category, $P(C|\mathbf{x}, T_r)$, by using (3.1.3), (3.1.4) and Table 3.1. These local posterior probabilities are then combined by using the Bayesian inference to obtain a global posterior probability for each category, i.e.,

$$
\begin{aligned}
P(C|\mathbf{x}) &= \sum_r P(C|\mathbf{x}, T_r) P(T_r|\mathbf{x}) \\
&= \sum_r P(C|\mathbf{x}, T_r) \frac{p(\mathbf{x}|T_r)P(T_r)}{p(\mathbf{x})} \\
&= \sum_r P(C|\mathbf{x}, T_r) \frac{\sum_C p(\mathbf{x}|C, T_r)P(C|T_r)P(T_r)}{p(\mathbf{x})} \\
&= \sum_r P(C|\mathbf{x}, T_r) \frac{\sum_C \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)}{p(\mathbf{x})} P(T_r) \qquad (3.2.1)
\end{aligned}
$$

where we have used (3.1.2) to obtain the last line of (3.2.1), and the a-priori probability of each terrain, $P(T_r)$, is assumed to be uniform among all terrains. Upon substitution of (3.1.3) into (3.2.1), $P(C|\mathbf{x})$ is then computed as:

$$
\begin{aligned}
P(C|\mathbf{x}) &= \sum_r \frac{\sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)P(T_r)}{p(\mathbf{x})} \\
&= \frac{1}{p(\mathbf{x})} \sum_r \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)P(T_r) \\
&\propto \sum_r \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r) \qquad (3.2.2)
\end{aligned}
$$

In summary, given an input feature vector $\mathbf{x}$, the Bayesian classifier first computes $p(\mathbf{x}|V_j, T_r)$ by using (3.1.4) for all V_j and T_r, then computes $\sum_r \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)$ for each category using Table 3.1 for $P(V_j|T_r)$, and finally compares all categories to determine the one associated with the maximum $\sum_r \sum_{V_j \in C} p(\mathbf{x}|V_j, T_r)P(V_j|T_r)$, to which $\mathbf{x}$ is assigned.

Table 3.1: Conditional probability of a kind of vehicle given an environmental condition.

Terrain	A	B	C	D
Heavy-tracked a	1/6	1/5	1/9	1/6
Heavy-tracked b	1/6	1/5	1/9	0
Heavy-Tracked c	1/6	1/5	1/9	1/6
Heavy-Tracked d	1/6	0	1/9	1/6
Light-Tracked a	0	0	1/9	1/6
Heavy-Wheeled a	0	0	1/9	0
Heavy-Wheeled b	1/6	1/5	1/9	1/6
Light-Wheeled a	0	1/5	1/9	1/6
Light-Wheeled b	1/6	0	1/9	0

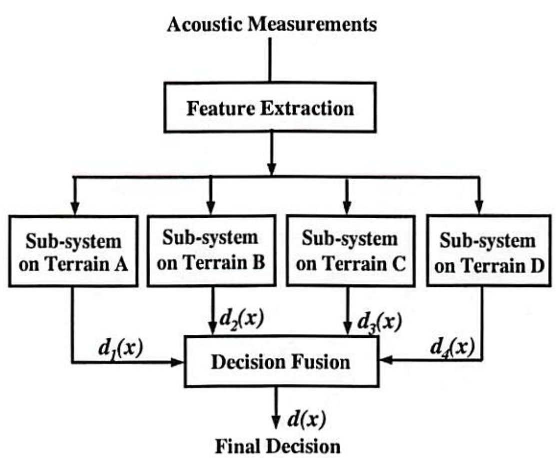


Figure 3.1: Classifier architecture for the multi-category classification of ground vehicles based on acoustic data of various environmental conditions.

Chapter 4

Classifier Designs: Fuzzy Logic Rule-Based Classifiers

The classifier architecture depicted in Fig. 3.1 can also be implemented by using fuzzy logic rule-based classifiers (FLRBC).

4.1 Sub-Systems

The FLRBC has four sub-systems, T_r ($r = 1, \ldots, 4$), each of which is responsible for the vehicle classification in one terrain, and is a separate and complete fuzzy logic rule-based system with its own fuzzification, rule-base, inference engine and output processing components. Although these four sub-systems have different numbers of rules, and different parameters for fuzzification (i.e., input models), antecedents and consequents, they have similar structure and operational mechanisms.

Rule Base: The rule base of the r-th ($r = 1, \ldots, 4$) sub-system has M_r fuzzy logic rules, each of which corresponds to one *kind* of vehicle in the terrain T_r and has the following form:

$$R^{j_r}\text{: IF } x_1 \text{ is } F_1^{j_r} \text{ and } x_2 \text{ is } F_2^{j_r} \text{ and } \cdots \text{ and } x_{11} \text{ is } F_{11}^{j_r}\text{, THEN } y \text{ is } \left[g_1^{j_r}, g_2^{j_r}\right]^t$$

where R^{j_r} represents the j-th rule of the r-th sub-system, $\mathbf{x} \equiv [x_1, \ldots, x_{11}]^t$ are the feature variables and y is the decision variable. The consequent $\left[g_1^{j_r}, g_2^{j_r}\right]^t$ modifying the attribute of the decision variable y is modeled as a two-dimensional vector of crisp numbers, and is initialized as $[+1, +1]^t$ ($[+1, -1]^t$, $[-1, +1]^t$ or $[-1, -1]^t$) if R^{j_r} corresponds to a heavy-tracked (light-tracked, heavy-wheeled or light-wheeled) vehicle. The antecedent $F_k^{j_r}$ modifying the k-th feature variable x_k ($k = 1, \ldots, 11$) can be modeled as either a type-1 or interval type-2 fuzzy set, depending on whether the FLRBC is implemented by using type-1 or interval type-2 fuzzy logic systems.

Fuzzification: Given an input feature vector $\mathbf{x}' \equiv [x'_1, x'_2, \ldots, x'_{11}]^t$ consisting of crisp measurements, the fuzzification process of the r-th ($r = 1, \ldots, 4$) sub-system is to convert x'_k ($k = 1, \ldots, 11$) to a fuzzy set A_k^r. Also, depending on whether the FLRBC is implemented by using type-1 or interval type-2 fuzzy logic systems, A_k^r can be either a type-1 or interval type-2 fuzzy set.

Inference Engine: The inference engine of the r-th ($r = 1, \ldots, 4$) sub-system computes the firing degree, f^{j_r} ($j_r = 1, \ldots, M_r$), for each rule that measures the degree of similarity between the input fuzzy sets, $A_1^r, A_2^r, \ldots, A_{11}^r$, and the antecedent fuzzy sets of the j_r-the rule, $F_1^{j_r}, F_2^{j_r}, \ldots, F_{11}^{j_r}$. Also, depending on whether the FLRBC is implemented by using type-1 or interval type-2 fuzzy logic systems, the firing degree f^{j_r} can be either a crisp number (a firing degree) or a sub-interval of the unit interval $[0, 1]$ (a firing interval).

Output Processing: The output processing of the FLRBC is used for decision fusion[1]. More specifically, the firing degrees, f^{j_r}, and the consequents, $\left[g_1^{j_r}, g_2^{j_r}\right]^t$, of all rules ($j_r = 1, \ldots, M_r$) of all sub-systems are simultaneously combined through output processing as if they were from the same fuzzy logic rule-based system, so as to obtain the global output $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$.

Note that in this output processing-based approach of decision fusion there are no local decisions from each sub-system, and the (global) decision for the input feature vector $\mathbf{x}'$ is made based on the signs of $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ according to Table 4.1.

When the FLRBC is implemented by using type-1 fuzzy logic systems, the output processing only includes defuzzification; whereas, when the FLRBC is implemented by using interval type-2 fuzzy logic systems, the output processing includes both type-reduction and defuzzification.

4.2 Type-1 and Interval Type-2 Implementations of the Fuzzy Logic Rule-Based Classifiers

In this section we provide details of computations involved in the type-1 and interval type-2 implementations of the FLRBC.

[1] We have also considered the majority voting-based approach of decision fusion, in which each sub-system first performs its own output processing so as to obtain the local decisions in terms of category labels, and the fusion center then combines these local decisions by using a majority vote to obtain the global decision. However, through the experiment for the type-1 FLRBC, we have found that this majority voting-based approach of decision fusion does not perform as well as the output processing-based approach of decision fusion. Therefore, we only discuss the latter approach here.

4.2.1 Type-1 FLRBC

Rule Base: In the type-1 implementation, the antecedents of each rule, $F_k^{j_r}$ ($k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$, and $r = 1, \ldots, 4$), are modeled as type-1 fuzzy sets whose membership functions (MF) are Gaussian centered at $m_k^{j_r}$ with standard deviation $\sigma_k^{j_r}$, i.e.,

$$F_k^{j_r} : \mu_k^{j_r}(x_k) = \exp\left\{-\frac{1}{2}\left(\frac{x_k - m_k^{j_r}}{\sigma_k^{j_r}}\right)^2\right\} \equiv \phi\left(x_k; m_k^{j_r}, \sigma_k^{j_r}\right) \tag{4.2.1}$$

Fuzzification: Given the input feature vector $\mathbf{x}' \equiv [x'_1, \ldots, x'_{11}]^t$, the r-th ($r = 1, \ldots, 4$) sub-system encodes x'_k ($k = 1, \ldots, 11$) as a type-1 fuzzy set A_k^r whose MF is Gaussian centered at x'_k with standard deviation σ_k^r, i.e.,

$$A_k^r : \mu_k^r(x_k) = \exp\left\{-\frac{1}{2}\left(\frac{x_k - x'_k}{\sigma_k^r}\right)^2\right\} \equiv \phi\left(x_k; x'_k, \sigma_k^r\right) \tag{4.2.2}$$

Fuzzy Inference: In the type-1 implementation, the firing degree of each rule, f^{j_r} ($j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$), is a value in the unit interval, i.e. [2],

$$f^{j_r} = \prod_{k=1}^{11} \sup_{x_k} \mu_k^r(x_k)\mu_k^{j_r}(x_k) = \prod_{k=1}^{11} \exp\left\{-\frac{\left(x'_k - m_k^{j_r}\right)^2}{2\left(\sigma_k^r\right)^2 + 2\left(\sigma_k^{j_r}\right)^2}\right\} \tag{4.2.3}$$

Output Processing: The output processing of the type-1 implementation only consists of defuzzification, i.e., the consequents ($\left[g_1^{j_r}, g_2^{j_r}\right]^t$) and firing degrees ($f^{j_r}$) of all rules ($j_r = 1, \ldots, M_r$) of all sub-systems ($r = 1, \ldots, 4$) are combined as follows [2]:

$$y_i(\mathbf{x}') = \sum_{r=1}^{4}\sum_{j_r=1}^{M_r} g_i^{j_r} f^{j_r} \Bigg/ \sum_{r=1}^{4}\sum_{j_r=1}^{M_r} f^{j_r}, \; i = 1 \text{ and } 2 \tag{4.2.4}$$

where $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ are the crisp output vector of the type-1 FLRBC for the input feature vector $\mathbf{x}'$.

Classification: The classification decision for the input feature vector $\mathbf{x}'$ is made based on the signs of $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ according to Table 4.1.

4.2.2 Interval Type-2 FLRBC

Rule Base: In the interval type-2 implementation, the antecedents of each rule, $\widetilde{F}_k^{j_r}$ ($k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$), is modeled as an interval type-2 fuzzy set[2] whose MF is Gaussian with uncertain mean ($m \in \left[m_{1,k}^{j_r}, m_{2,k}^{j_r}\right]$) and uncertain standard deviation ($\sigma \in \left[\sigma_{1,k}^{j_r}, \sigma_{2,k}^{j_r}\right]$). The lower and upper MFs (LMF and UMF) of $\widetilde{F}_k^{j_r}$, $\underline{\mu}_k^{j_r}(x_k)$ and $\overline{\mu}_k^{j_r}(x_k)$, are given as [4, 5]:

$$\underline{\mu}_k^{j_r}(x_k) = \begin{cases} \phi\left(x_k; m_{2,k}^{j_r}, \sigma_{1,k}^{j_r}\right) & \text{if } x_k \leq \left(m_{1,k}^{j_r} + m_{2,k}^{j_r}\right)/2 \\ \phi\left(x_k; m_{1,k}^{j_r}, \sigma_{1,k}^{j_r}\right) & \text{if } x_k > \left(m_{1,k}^{j_r} + m_{2,k}^{j_r}\right)/2 \end{cases} \tag{4.2.5}$$

$$\overline{\mu}_k^{j_r}(x_k) = \begin{cases} \phi\left(x_k; m_{1,k}^{j_r}, \sigma_{2,k}^{j_r}\right) & \text{if } x_k \leq m_{1,k}^{j_r} \\ 1 & \text{if } m_{1,k}^{j_r} < x_k \leq m_{2,k}^{j_r} \\ \phi\left(x_k; m_{2,k}^{j_r}, \sigma_{2,k}^{j_r}\right) & \text{if } x_k > m_{2,k}^{j_r} \end{cases} \tag{4.2.6}$$

Fuzzification: Given the input feature vector $\mathbf{x}' \equiv [x_1', \ldots, x_{11}']^t$, the r-th ($r = 1, \ldots, 4$) sub-system encodes x_k' ($k = 1, \ldots, 11$) as an interval type-2 fuzzy set $\widetilde{A}_k^r$ whose MF is Gaussian centered at x_k' with uncertain standard deviation $\sigma \in \left[\sigma_{1,k}^r, \sigma_{2,k}^r\right]$. The LMF and UMF of $\widetilde{A}_k^r$, $\underline{\mu}_k^r(x_k)$ and $\overline{\mu}_k^r(x_k)$, are given as:

$$\underline{\mu}_k^r(x_k) = \phi\left(x_k; x_k', \sigma_{1,k}^r\right) \tag{4.2.7}$$

$$\overline{\mu}_k^r(x_k) = \phi\left(x_k; x_k', \sigma_{2,k}^r\right) \tag{4.2.8}$$

Fuzzy Inference: In the interval type-2 implementation, the firing degree of each rule is a sub-interval of the unit interval, a firing interval, and is characterized by the lower and

[2] An interval type-2 fuzzy set is usually represented by an upper case letter with tilde.

upper firing degrees, $\underline{f}^{j_r}$ and $\overline{f}^{j_r}$ ($j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$), that are computed as [2]:

$$\underline{f}^{j_r} = \prod_{k=1}^{j_r} \sup_{x_k} \underline{\mu}_k^r(x_k)\underline{\mu}_k^{j_r}(x_k) \tag{4.2.9}$$

$$\overline{f}^{j_r} = \prod_{k=1}^{j_r} \sup_{x_k} \overline{\mu}_k^r(x_k)\overline{\mu}_k^{j_r}(x_k) \tag{4.2.10}$$

where the computations of $\sup_{x_k} \underline{\mu}_k^r(x_k)\underline{\mu}_k^{j_r}(x_k)$ and $\sup_{x_k} \overline{\mu}_k^r(x_k)\overline{\mu}_k^{j_r}(x_k)$ for the LMFs and UMFs of (4.2.5)-(4.2.8) are provided as in Table 4.2.

Output Processing: The output processing of the interval type-2 implementation consists of type-reduction and defuzzification.

Type-reduction combines the lower and upper firing degrees ($\underline{f}^{j_r}$ and $\overline{f}^{j_r}$) and the consequents ($\left[g_1^{j_r}, g_2^{j_r}\right]^t$) of all rules ($j_r = 1, \ldots, M_r$) of all sub-systems ($r = 1, \ldots, 4$) to obtain the type-reduced output, $[y_{1,l}(\mathbf{x}'), y_{1,r}(\mathbf{x}')]$ and $[y_{2,l}(\mathbf{x}'), y_{2,r}(\mathbf{x}')]$. Although there is no closed form formulas, and we must apply the Kanik-Mendel iterative procedure to compute the type-reduced output [2], we can still express $y_{i,l}(\mathbf{x}')$ and $y_{i,r}(\mathbf{x}')$ ($i = 1$ and 2) as follows [5]:

$$y_{i,l} = \left\{\sum_{r=1}^{4}\sum_{j_r=1}^{M_r} g_i^{j_r}\left[\delta_{i,l}^{j_r}\overline{f}^{j_r} + \left(1-\delta_{i,l}^{j_r}\right)\underline{f}^{j_r}\right]\right\} \Big/ \left\{\sum_{r=1}^{4}\sum_{j_r=1}^{M_r}\left[\delta_{i,l}^{j_r}\overline{f}^{j_r} + \left(1-\delta_{i,l}^{j_r}\right)\underline{f}^{j_r}\right]\right\} \tag{4.2.11}$$

$$y_{i,r} = \left\{\sum_{r=1}^{4}\sum_{j_r=1}^{M_r} g_i^{j_r}\left[\delta_{i,r}^{j_r}\overline{f}^{j_r} + \left(1-\delta_{i,r}^{j_r}\right)\underline{f}^{j_r}\right]\right\} \Big/ \left\{\sum_{r=1}^{4}\sum_{j_r=1}^{M_r}\left[\delta_{i,r}^{j_r}\overline{f}^{j_r} + \left(1-\delta_{i,r}^{j_r}\right)\underline{f}^{j_r}\right]\right\} \tag{4.2.12}$$

where $\delta_{i,l}^{j_r}$ and $\delta_{i,r}^{j_r}$ indicate whether the upper (when they take the value of 1) or lower (when they take the value of 0) firing degree of the j_r-th rule is used during the computation of $y_{i,l}(\mathbf{x}')$ and $y_{i,r}(\mathbf{x}')$, respectively, and are defined based on the values of $y_{i,l}(\mathbf{x}')$ and $y_{i,r}(\mathbf{x}')$

as follows:

$$\delta_{i,l}^{j_r} = \begin{cases} 1 & \text{if} \quad g_i^{j_r} \leq y_{i,l}(\mathbf{x}') \\ 0 & \text{otherwise} \end{cases} \tag{4.2.13}$$

$$\delta_{i,r}^{j_r} = \begin{cases} 1 & \text{if} \quad g_i^{j_r} \geq y_{i,r}(\mathbf{x}') \\ 0 & \text{otherwise} \end{cases} \tag{4.2.14}$$

Note that (4.2.11)-(4.2.14) cannot be used to compute the type-reduced set because $\delta_{i,l}^{j_r}$ and $\delta_{i,r}^{j_r}$ can only be determined after $y_{i,l}(\mathbf{x}')$ and $y_{i,r}(\mathbf{x}')$ are determined through the Karnik-Mendel iterative procedure, but they can be used to compute the partial derivatives of the type-reduced output with respect to the parameters (as shown in the next section).

Defuzzification obtains the crisp output vector, $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$, from the type-reduced output, $[y_{i,l}(\mathbf{x}'), y_{i,r}(\mathbf{x}')]$ ($i = 1$ and 2), as follows:

$$y_i(\mathbf{x}') = [y_{i,l}(\mathbf{x}') + y_{i,r}(\mathbf{x}')]/\,2 \tag{4.2.15}$$

Classification: Similar to the type-1 FLRBC, the classification decision for the input feature vector $\mathbf{x}'$ is made based on the signs of $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ according to Table 4.1.

4.3 Parameter Initialization and Optimization

4.3.1 Parameter Initialization

Type-1 FLRBC: There are totally 668 parameters in the type-1 FLRBC to be initialized and optimized, including the consequent, $[g_1^{j_r}, g_2^{j_r}]^t$, antecedent, $\{m_k^{j_r}, \sigma_k^{j_r}\}$, and input parameters, σ_k^r ($k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$, where $M_r = 6$, 5, 9 and 6 for terrain A, B, C and D, respectively).

The consequent parameters, $\left[g_1^{j_r}, g_2^{j_r}\right]^t$ ($j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$), are initialized as $[+1, +1]^t$ ($[+1, -1]^t$, $[-1, +1]^t$, or $[-1, -1]^t$) if j_r (the j-th vehicle on the r-th terrain) corresponds to a heavy-tracked (light-tracked, heavy-wheeled, or light-wheeled) vehicle. The other parameters of the type-1 FLRBC, including the antecedent parameters $\{m_k^{j_r}, \sigma_k^{j_r}\}$ and input parameters σ_k^r ($k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$), are initialized based on the statistics of the training prototypes as:

$$m_k^{j_r}(0) = \frac{1}{N^{j_r}} \sum_{\mathbf{x} \in V^{j,r}} x_k \tag{4.3.1}$$

$$\sigma_k^{j_r}(0) = \sqrt{\frac{1}{N^{j_r} - 1} \sum_{\mathbf{x} \in V^{j_r}} \left(x_k - m_k^{j_r}\right)^2} \tag{4.3.2}$$

$$\sigma_k^r(0) = \frac{1}{M_r} \sum_{j_r=1}^{M_r} \sigma_k^{j_r} \tag{4.3.3}$$

where $m_k^{j_r}(0)$, $\sigma_k^{j_r}(0)$ and $\sigma_k^r(0)$ represent the initial values of $m_k^{j_r}$, $\sigma_k^{j_r}$ and σ_k^r, respectively, V^{j_r} represents the set of the training prototypes corresponding to the j-th vehicle on the r-th terrain, N^{j_r} is the number of prototypes of V^{j_r}, and x_k is the k-th element (corresponding to the k-th feature) of $\mathbf{x}$.

Type-2 FLRBC: There are totally 1,284 parameters in the interval type-2 FLRBC to be initialized and optimized, including the consequent $\left[g_1^{j_r}, g_2^{j_r}\right]^t$, antecedent, $\{m_{1,k}^{j_r}, m_{2,k}^{j_r}, \sigma_{1,k}^{j_r}, \sigma_{2,k}^{j_r}\}$, and input parameters, $\{\sigma_{1,k}^r, \sigma_{2,k}^r\}$ ($k = 1, \ldots, 11$, $j_1 = 1, \ldots, M_r$, and $r = 1, \ldots, 4$).

The parameters of the interval type-2 FLRBC are initialized based on the parameters of the competing type-1 FLRBC that have been optimized through training and testing, as:

$$g_1^{j_r}(0) = g_1^{j_r}(\text{optimial}) \qquad g_2^{j_r}(0) = g_2^{j_r}(\text{optimial}) \tag{4.3.4}$$

$$m_{1,k}^{j_r}(0) = m_k^{j_r}(\text{optimal}) - \gamma\sigma_k^{j_r}(\text{optimal}) \tag{4.3.5}$$

$$m_{2,k}^{j_r}(0) = m_k^{j_r}(\text{optimal}) + \gamma\sigma_k^{j_r}(\text{optimal}) \tag{4.3.6}$$

$$\sigma_{1,k}^{j_r}(0) = (1-\gamma)\sigma_k^{j_r}(\text{optimal}) \qquad \sigma_{2,k}^{j_r}(0) = (1+\gamma)\sigma_k^{j_r}(\text{optimal}) \tag{4.3.7}$$

$$\sigma_{1,k}^{r}(0) = (1-\gamma)\sigma_k^{r}(\text{optimal}) \qquad \sigma_{2,k}^{r}(0) = (1+\gamma)\sigma_k^{r}(\text{optimal}) \tag{4.3.8}$$

where the left hand sides of all equations correspond to the initial values of the interval type-2 FLRBC, the right hand sides of all equations correspond to the parameters of the type-1 FLRBC that have been optimized, and γ has been chosen as 0.1.

4.3.2 Parameter Optimization

We have used a steepest descent algorithm to optimize the parameters of the FLRBC, which is based on the computations of the partial derivatives of the output with respect to the parameters. More specifically, given a training prototype characterized by its feature vector $\mathbf{x}'$, we define the classification error $e(\mathbf{x}')$ as:

$$e(\mathbf{x}') \equiv \frac{1}{2}\left[d_1(\mathbf{x}') - y_1(\mathbf{x}')\right]^2 + \frac{1}{2}\left[d_2(\mathbf{x}') - y_2(\mathbf{x}')\right]^2 \tag{4.3.9}$$

where $[d_1(\mathbf{x}'), d_2(\mathbf{x}')]^t$ is the desired classification result that is $[+1,+1]^t$, $[+1,-1]^t$, $[-1,+1]^t$ or $[-1,-1]^t$ when $\mathbf{x}'$ is from a heavy-tracked, light-tracked, heavy-wheeled or light-wheeled vehicle, respectively, and $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ is the crisp output vector out of the FLRBC. The steepest descent algorithm updates the parameters of the FLRBC as:

$$\theta(\text{updated}) = \theta(\text{old}) - \alpha \left.\frac{\partial e}{\partial \theta}\right|_{\theta(\text{old})} = \theta(\text{old}) + \alpha \sum_{i=1}^{2}\left[d_i(\mathbf{x}') - y_i(\mathbf{x}')\right] \left.\frac{\partial y_i}{\partial \theta}\right|_{\theta(\text{old})} \tag{4.3.10}$$

where θ represents any parameter in the FLRBC to be optimized, and the step size α is a positive number[3].

Since we have used the firing degrees and the consequents of all rules from all sub-systems to obtain the output, the partial derivatives of the output with respect to the parameters of any sub-system involves not only the parameters of the sub-system being focused on, but also the parameters of the other sub-systems, as demonstrated below.

Partial Derivatives of the Type-1 FLRBC: The parameters of the type-1 FLRBC include the ones for fuzzification, σ_k^r, antecedents, $\{m_k^{j_r}, \sigma_k^{j_r}\}$, and consequents, $\{g_1^{j_r}, g_2^{j_r}\}$ ($k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$). By using (4.2.3) and/or (4.2.4), we compute the partial derivatives of the output $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ with respect to these parameters as:

$$\frac{\partial y_i(\mathbf{x}')}{\partial g_i^{j_r}} = f^{j_r} \Big/ \sum_{r=1}^{4} \sum_{q_r=1}^{M_r} f^{q_r} \tag{4.3.11}$$

$$\frac{\partial y_i(\mathbf{x}')}{\partial \theta_k^{j_r}} = \left[(g_i^{j_r} - y_i(\mathbf{x}')) / \sum_{q_r=1}^{M_r} f^{q_r} \right] \partial f^{j_r} / \partial \theta_k^{j_r} \tag{4.3.12}$$

$$\frac{\partial y_i(\mathbf{x}')}{\partial \sigma_k^r} = \sum_{j_r=1}^{M_r} \left[(g_i^{j_r} - y_i(\mathbf{x}')) / \sum_{q_r=1}^{M_r} f^{q_r} \right] \partial f^{j_r} / \partial \sigma_k^r \tag{4.3.13}$$

where $\theta_k^{j_r}$ represents the antecedent parameter of the j_r-th rule corresponding to the k-the feature variable (i.e., either $m_k^{j_r}$ or $\sigma_k^{j_r}$), and the equations for $\partial f^{j_r} / \partial \theta_k^{j_r}$ and $\partial f^{j_r} / \partial \sigma^r$ are given in Appendix A of [5]. Observe from (4.3.11)-(4.3.13) that the partial derivatives of the output with respect to the parameters of the r-th subsystem depend not only on the parameters of the subsystem being focused on, but also on the parameters of the other subsystems through the summation $\sum_{r=1}^{4} \sum_{j_r=1}^{M_r} f^{j_r}$.

[3] In the experiments, we set $\alpha = 2 \times$ testing classification error.

Partial Derivatives of the Interval Type-2 FLRBC: The parameters of the interval type-2 FLRBC also include the ones for fuzzification, $\{\sigma^r_{1,k}, \sigma^r_{2,k}\}$, antecedents, $\{m^{j_r}_{1,k}, m^{j_r}_{2,k}, \sigma^{j_r}_{1,k}, \sigma^{j_r}_{2,k}\}$, and consequents, $\{g^{j_r}_1, g^{j_r}_2\}$ ($k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$ and $r = 1, \ldots, 4$). By using (4.2.11)-(4.2.15), we compute the partial derivatives of the output $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$ with respect to these parameters as:

$$\frac{\partial y_i(\mathbf{x}')}{\partial g^{j_r}_i} = \frac{1}{2}\left[\frac{\partial y_{i,l}(\mathbf{x}')}{\partial g^{j_r}_i} + \frac{\partial y_{i,r}(\mathbf{x}')}{\partial g^{j_r}_i}\right] \tag{4.3.14}$$

$$\frac{\partial y_{i,l}(\mathbf{x}')}{\partial g^{j_r}_i} = \left[\delta^{j_r}_{i,l}\overline{f}^{j_r} + \left(1-\delta^{j_r}_{i,l}\right)\underline{f}^{j_r}\right] \Big/ \sum_{r=1}^{4}\sum_{q_r=1}^{M_r}\left[\delta^{q_r}_{i,l}\overline{f}^{q_r} + \left(1-\delta^{q_r}_{i,l}\right)\underline{f}^{j_r}\right] \tag{4.3.15}$$

$$\frac{\partial y_{i,r}(\mathbf{x}')}{\partial g^{j_r}_i} = \left[\delta^{j_r}_{i,r}\overline{f}^{j_r} + \left(1-\delta^{j_r}_{i,r}\right)\underline{f}^{j_r}\right] \Big/ \sum_{r=1}^{4}\sum_{q_r=1}^{M_r}\left[\delta^{q_r}_{i,r}\overline{f}^{q_r} + \left(1-\delta^{q_r}_{i,r}\right)\underline{f}^{j_r}\right] \tag{4.3.16}$$

$$\frac{\partial y_i(\mathbf{x}')}{\partial \theta^{j_r}_k} = \frac{1}{2}\left[\frac{\partial y_{i,l}(\mathbf{x}')}{\partial \theta^{j_r}_k} + \frac{\partial y_{i,r}(\mathbf{x}')}{\partial \theta^{j_r}_k}\right] \tag{4.3.17}$$

$$\begin{aligned}\frac{\partial y_{i,l}(\mathbf{x}')}{\partial \theta^{j_r}_k} =& \left\{\delta^{j_r}_{i,l}\left[g^{j_r}_i - y^{j_r}_{i,l}\right] / \sum_{r=1}^{4}\sum_{q_r=1}^{M_r}\left[\delta^{q_r}_{i,l}\overline{f}^{q_r} + \left(1-\delta^{q_r}_{i,l}\right)\underline{f}^{j_r}\right]\right\} \partial\overline{f}^{j_r} \Big/ \partial\theta^{j_r}_k \\ &+ \left\{\left(1-\delta^{j_r}_{i,l}\right)\left[g^{j_r}_i - y^{j_r}_{i,l}\right] / \sum_{r=1}^{4}\sum_{q_r=1}^{M_r}\left[\delta^{q_r}_{i,l}\overline{f}^{q_r} + \left(1-\delta^{q_r}_{i,l}\right)\underline{f}^{j_r}\right]\right\} \partial\underline{f}^{j_r} / \partial\theta^{j_r}_k\end{aligned} \tag{4.3.18}$$

$$\begin{aligned}\frac{\partial y_{i,r}(\mathbf{x}')}{\partial \theta^{j_r}_k} =& \left\{\delta^{j_r}_{i,r}\left[g^{j_r}_i - y^{j_r}_{i,r}\right] / \sum_{r=1}^{4}\sum_{q_r=1}^{M_r}\left[\delta^{q_r}_{i,r}\overline{f}^{q_r} + \left(1-\delta^{q_r}_{i,r}\right)\underline{f}^{j_r}\right]\right\} \partial\overline{f}^{j_r} \Big/ \partial\theta^{j_r}_k \\ &+ \left\{\left(1-\delta^{j_r}_{i,r}\right)\left[g^{j_r}_i - y^{j_r}_{i,r}\right] / \sum_{r=1}^{4}\sum_{q_r=1}^{M_r}\left[\delta^{q_r}_{i,r}\overline{f}^{q_r} + \left(1-\delta^{q_r}_{i,r}\right)\underline{f}^{j_r}\right]\right\} \partial\underline{f}^{j_r} / \partial\theta^{j_r}_k\end{aligned} \tag{4.3.19}$$

$$\frac{\partial y_i(\mathbf{x}')}{\partial \theta^{r}_k} = \frac{1}{2}\left[\frac{\partial y_{i,l}(\mathbf{x}')}{\partial \theta^{r}_k} + \frac{\partial y_{i,r}(\mathbf{x}')}{\partial \theta^{r}_k}\right] \tag{4.3.20}$$

$$\frac{\partial y_{i,l}(\mathbf{x}')}{\partial \theta_k^r} = \sum_{j_r=1}^{M_r} \left\{ \delta_{i,l}^{j_r} \left[g_i^{j_r} - y_{i,l}^{j_r}\right] / \sum_{r=1}^{4} \sum_{q_r=1}^{M_r} \left[\delta_{i,l}^{q_r} \overline{f}^{q_r} + \left(1 - \delta_{i,l}^{q_r}\right) \underline{f}^{j_r}\right] \right\} \partial \overline{f}^{j_r} \Big/ \partial \theta_k^r \quad (4.3.21)$$

$$+ \sum_{j_r=1}^{M_r} \left\{ \left(1 - \delta_{i,l}^{j_r}\right) \left[g_i^{j_r} - y_{i,l}^{j_r}\right] / \sum_{r=1}^{4} \sum_{q_r=1}^{M_r} \left[\delta_{i,l}^{q_r} \overline{f}^{q_r} + \left(1 - \delta_{i,l}^{q_r}\right) \underline{f}^{j_r}\right] \right\} \partial \underline{f}^{j_r} / \partial \theta_k^r$$

$$\frac{\partial y_{i,r}(\mathbf{x}')}{\partial \theta_k^r} = \sum_{j_r=1}^{M_r} \left\{ \delta_{i,r}^{j_r} \left[g_i^{j_r} - y_{i,r}^{j_r}\right] / \sum_{r=1}^{4} \sum_{q_r=1}^{M_r} \left[\delta_{i,r}^{q_r} \overline{f}^{q_r} + \left(1 - \delta_{i,r}^{q_r}\right) \underline{f}^{j_r}\right] \right\} \partial \overline{f}^{j_r} \Big/ \partial \theta_k^r \quad (4.3.22)$$

$$+ \sum_{j_r=1}^{M_r} \left\{ \left(1 - \delta_{i,r}^{j_r}\right) \left[g_i^{j_r} - y_{i,r}^{j_r}\right] / \sum_{r=1}^{4} \sum_{q_r=1}^{M_r} \left[\delta_{i,r}^{q_r} \overline{f}^{q_r} + \left(1 - \delta_{i,r}^{q_r}\right) \underline{f}^{j_r}\right] \right\} \partial \underline{f}^{j_r} / \partial \theta_k^r$$

where $\theta_k^{j_r}$ represents the antecedent parameters of the j_r-th rule corresponding to the k-th feature variable (i.e., $m_{1,k}^{j_r}$, $m_{2,k}^{j_r}$, $\sigma_{1,k}^{j_r}$ or $\sigma_{2,k}^{j_r}$), and θ_k^r represent the input parameters corresponding to the k-th feature variable in the r-th sub-system (i.e., either $\sigma_{1,k}^{j_r}$ or $\sigma_{2,k}^{j_r}$), and the formulas for computing $\partial \underline{f}^{j_r} / \partial \theta_k^{j_r}$, $\partial \overline{f}^{j_r} \Big/ \partial \theta_k^{j_r}$, $\partial \underline{f}^{j_r} / \partial \theta_k^r$, and $\partial \overline{f}^{j_r} \Big/ \partial \theta_k^r$ are provided in Appendix C of [5]. Observe from (4.3.14)-(4.3.22) that the partial derivatives of the output $y_i(\mathbf{x}')$ with respect to the parameters of the r-th sub-system (including $g_i^{j_r}$, $\theta_k^{j_r}$ and θ_k^r for $k = 1, \ldots, 11$, $j_r = 1, \ldots, M_r$, $i = 1$ and 2) depend not only on the parameters of the sub-system being focused on, but also on the parameters of the other sub-systems through the summations $\sum_{r=1}^{4} \sum_{j_r=1}^{M_r} \left[\delta_{i,l}^{j_r} \overline{f}^{j_r} + \left(1 - \delta_{i,l}^{j_r}\right) \underline{f}^{j_r}\right]$ and $\sum_{r=1}^{4} \sum_{j_r=1}^{M_r} \left[\delta_{i,r}^{j_r} \overline{f}^{j_r} + \left(1 - \delta_{i,r}^{j_r}\right) \underline{f}^{j_r}\right]$.

Using the just computed partial derivatives for both the type-1 and interval type-2 FLRBCs, we have optimized the parameter of the r-th sub-system by using the training prototypes of the r-th terrain as well as of all the other terrains in steepest descent algorithms. In this way, we have optimized the performance of the entire (type-1 or interval type-2) FLRBC across all four terrains.

Table 4.1: Decision for the input feature vector $\mathbf{x}'$ based on $[y_1(\mathbf{x}'), y_2(\mathbf{x}')]^t$.

Decision	$y_1(\mathbf{x}')$	$y_2(\mathbf{x}')$
heavy-tracked	positive	positive
light-tracked	positive	negative
heavy-wheeled	negative	positive
light-wheeled	negative	negative

Table 4.2: Computations of $\sup_{x_k} \underline{\mu}_k^r(x_k)\underline{\mu}_k^{jr}(x_k)$ and $\sup_{x_k} \overline{\mu}_k^r(x_k)\overline{\mu}_k^{jr}(x_k)$ for the LMFs and UMFs of (4.2.5)-(4.2.8).

$\sup_{x_k} \underline{\mu}_k^r(x_k)\underline{\mu}_k^{jr}(x_k)$

Location	$\sup_{x_k} \underline{\mu}_k^r(x_k)\underline{\mu}_k^{jr}(x_k)$
$x_k' \leq \frac{m_{1,k}^{jr}+m_{2,k}^{jr}}{2} - \frac{\left(\sigma_{1,k}^r\right)^2\left(m_{2,k}^{jr}-m_{1,k}^{jr}\right)}{2\left(\sigma_{1,k}^{jr}\right)^2}$	$\phi\left(x_k'; m_{2,k}^{jr}, \sqrt{\left(\sigma_{1,k}^r\right)^2+\left(\sigma_{1,k}^{jr}\right)^2}\right)$
$x_k' \geq \frac{m_{1,k}^{jr}+m_{2,k}^{jr}}{2} + \frac{\left(\sigma_{1,k}^r\right)^2\left(m_{2,k}^{jr}-m_{1,k}^{jr}\right)}{2\left(\sigma_{1,k}^{jr}\right)^2}$	$\phi\left(x_k'; m_{1,k}^{jr}, \sqrt{\left(\sigma_{1,k}^r\right)^2+\left(\sigma_{1,k}^{jr}\right)^2}\right)$
otherwise	$\exp\left\{-\frac{\left(m_{2,k}^{jr}-m_{1,k}^{jr}\right)^2}{8\left(\sigma_{1,k}^{jr}\right)^2} - \frac{\left(2x_k'-m_{1,k}^{jr}-m_{2,k}^{jr}\right)^2}{8\left(\sigma_{1,k}^r\right)^2}\right\}$

$\sup_{x_k} \overline{\mu}_k^r(x_k)\overline{\mu}_k^{jr}(x_k)$

x_k' Location	$\sup_{x_k} \overline{\mu}_k^r(x_k)\overline{\mu}_k^{jr}(x_k)$
$x_k' \leq m_{1,k}^{jr}$	$\phi\left(x_k'; m_{1,k}^{jr}, \sqrt{\left(\sigma_{2,k}^r\right)^2+\left(\sigma_{2,k}^{jr}\right)^2}\right)$
$x_k' \geq m_{2,k}^{jr}$	$\phi\left(x_k'; m_{2,k}^{jr}, \sqrt{\left(\sigma_{2,k}^r\right)^2+\left(\sigma_{2,k}^{jr}\right)^2}\right)$
otherwise	1

Chapter 5

Experiments and Results

We have performed experiments to evaluate the performance of the Bayesian classifier, type-1 and interval type-2 FLRBCs for the multi-category classification of ground vehicles based on the acoustic data of multiple-terrains.

5.1 Experiment of Leaving Out One Run From Each Terrain

In this experiment, we have randomly chosen one run from each terrain (totally four runs) to use their CPA-based prototypes for testing, and used the CPA-based prototypes of the remaining runs for training. Because there are 42, 27, 89 and 39 runs in the four terrains, respectively, there are $42 \times 27 \times 89 \times 39 = 3,936,114$ possible ways to choose testing runs, each of which leads to one particular classifier *design* (i.e., one configuration of the parameters). We have only experimented on 869 such designs. The pseudo-code for this experiment is described as follows:

for t =1:869 *// 869 designs in total*

{ Randomly pick one run from each terrain, and use their CPA-based prototypes for testing;

Use CPA-based prototypes of the remaining runs for training;

// Estimate the parameters and evaluate the performance of the Bayesian classifier;

Estimate the parameters $[\theta_B(t)]$ of the Bayesian classifier by using the training prototypes;

Evaluate the classification error rate $e_B(t)$ corresponding to $\theta_B(t)$ by using the testing prototypes;

// Train the parameters and evaluate the performance of the type-1 FLRBC;

Initialize the parameters $[\theta_1(t)]$ of the type-1 FLRBC;

Evaluate the classifier error rate $e_1(t)$ corresponding to $\theta_1(t)$ by using the testing prototypes;

// Keep training and testing until the parameters have been trained/tested for 1000 epochs or there have been no improvements for 200 epochs;

Set the counter of training epochs, $\text{Counter}_{\text{epoch}}$, to be 0;

Set the counter of no improvements, $\text{Counter}_{\text{no improvements}}$, to be 0;

While ($\text{Counter}_{\text{epoch}} < 1000$ and $\text{Counter}_{\text{no improvements}} < 200$)

{ Let $\text{Counter}_{\text{epoch}}$ = $\text{Counter}_{\text{epoch}}$+1;

Train the parameters of the type-1 FLRBC by using the training prototypes, and let the resulting parameters be θ_{temp};

Evaluate the classification error rate e_{temp} corresponding to θ_{temp};

If ($e_{\text{temp}} < e_1(t)$)

{ Set $\theta_1(t)$ to be θ_{temp};

Set $e_1(t)$ to be e_{temp}; }

Else

{ Let $\text{Counter}_{\text{no improvements}}$ = $\text{Counter}_{\text{no improvements}}$+1; }

```
    }
  // Train the parameters and evaluate the performance of the interval type-2 FLRBC;
  Initialize the parameters [θ2(t)] of the interval type-2 FLRBC based on
    the optimal parameters of the type-1 FLRBC θ1(t);
  Evaluate the classifier error rate e2(t) corresponding to θ2(t) by using
    the testing prototypes;
  // Keep training and testing until the parameters have been trained/tested for
    1000 epochs or there have been no improvements for 200 epochs;
  Set the counter of training epochs, Counter_epoch, to be 0;
  Set the counter of no improvements, Counter_no improvements, to be 0;
  While ( Counter_epoch < 1000 and Counter_no improvements < 200 )
    { Let Counter_epoch = Counter_epoch+1;
      Train the parameters of the interval type-2 FLRBC by using the
        training prototypes, and let the resulting parameters be θ_temp;
      Evaluate the classification error rate e_temp corresponding to θ_temp;
      If ( e_temp < e2(t) )
        { Set θ2(t) to be θ_temp;
          Set e2(t) to be e_temp; }
      Else
        { Let Counter_no improvements = Counter_no improvements+1; }
    }
}
Compute the mean and standard deviation of eB(t) , e1(t) and e2(t) over t = 1,...,869.
```

The mean and standard deviation of the classification error rates [i.e, $e_B(t)$, $e_1(t)$ and $e_2(t)$] over the 869 designs are summarized in Table 5.1.

For comparison, we have also included the results of the leave-one-run-out experiment for the multi-category classification of ground vehicles based on the acoustic data of the *normal* terrain (Table 8.1 of [5]) in Table 5.2.

Observe from Tables 5.1 and 5.2 that:

- Both the type-1 and interval type-2 FLRBCs have better performance than the Bayesian classifier, and the interval type-2 FLRBC has better performance than the type-1 FLRBC, where by *better* we mean smaller average and standard deviation of classification error rates over the 869 designs.

- It is very surprising that the Bayesian classifier for multiple-terrains has better performance than the Bayesian classifier for the normal terrain, even though the data in the former case are more uncertain than in the latter case. We have no explanation for this.

- The type-1 (or interval type-2) FLRBC for multiple-terrains cannot perform as good as the type-1 (or interval type-2) FLRBC for the normal terrain, even though the former has been trained using more epochs. This is consistent with our expectations, since the data of multiple-terrains are more uncertain than the data of the normal terrain.

During the first year of our study, for the binary classification problems, we performed the *leave-M-out* experiment (M is the number of different kinds of vehicles, and M equals 9, 5 and 4 for the tracked versus wheeled, heavy-tracked versus light-tracked, and heavy-wheeled versus light-wheeled classification problems, respectively). During the second year of our study, for the multi-category classification problem, we performed the *leave-two-out* and *10-fold cross validation* experiments. This year, for the multi-category classification problem based on the acoustic data of multiple-terrains, because there are more training data from all four terrains, the FLRBCs have more complicated architectures, and we have allowed more training epochs, it has taken us an extremely long time to run the simulation experiment

(With the computational capacity of our group, it took approximately 30 minutes to one hour to complete one design of the type-1 FLRBC, and one and a half to two and a half hours to complete one design of the interval type-2 FLRBC); hence, we have not performed other experiments as we did in the first two years of our study.

5.2 Experiment of Non-Adaptive and Adaptive Working Modes

So far we have designed the classifier in the way that the decision for each prototype only depends on its own features, which we call the *non-adaptive* working mode in the rest of this report. We have found during the first two years of our study that even the very simple *majority vote-based adaptive* working mode can greatly improve the classification performance [4, 5]. In this adaptive working mode, the classification decision for each prototype depends on not only the prototype itself but also some other prototypes of the same run. More specifically, let $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n, \ldots$ be the prototypes of the same run, and $s_1, s_2, \ldots, s_n, \ldots$ be their corresponding non-adaptive decisions (i.e., s_n is made by using $\mathbf{x}_n$ only),

- In the Bayesian classifier, each non-adaptive decision s_n $(n = 1, 2, \ldots)$ is in the form of a category label (e.g., *heavy-tracked*, *light-wheeled*). The adaptive decision for $\mathbf{x}_n$, s_n^a, is obtained by taking a majority vote on $s_1, s_2, \ldots, s_{n-1}, s_n$, i.e., s_n^a is *heavy-tracked* (*light-tracked*, *heavy-wheeled* or *light-wheeled*) if and only if more than half of $\{s_1, s_2, \ldots, s_{n-1}, s_n\}$ are *heavy-tracked* (*light-tracked*, *heavy-wheeled* or *light-wheeled*), and is un-specified if there is no category having more than half of votes.

- In the FLRBC, each non-adaptive decision s_n $(n = 1, 2, \ldots)$ is in the form of a two-dimensional vector (e.g., [positive, positive] represents the *heavy-tracked* vehicles, see

Table 4.1). The adaptive decision for $\mathbf{x}_n$, s_n^a, is also a two-dimensional vector that is obtained by taking a majority vote in each dimension, i.e., the element of s_n^a is positive (or negative) if and only if more than half of $\{s_1, s_2, \ldots, s_{n-1}, s_n\}$ are positive (or negative) in that dimension. The signs of the elements of s_n^a are mapped to the category label according to Table 4.1.

We have conducted the following experiment to examine both the non-adaptive and adaptive working modes for the multi-category classification of ground vehicles based on the acoustic data of multiple-terrains.

```
for t =1:200 // 200 designs in total
  { Randomly pick one run from each terrain, and use their CPA-based prototypes
      for testing;
    Use CPA-based prototypes of the remaining runs for training;
    // Estimate the parameters and evaluate the performance of the Bayesian classifier;
    Estimate the parameters [θ_B(t)] of the Bayesian classifier by using the
      training prototypes;
    Evaluate the non-adaptive classification error rate e_B(t) corresponding to
      θ_B(t) by using the testing prototypes;
    Evaluate the adaptive classification error rate e^a_B(t) corresponding to θ_B(t)
      by using the testing prototypes;
    // Train the parameters and evaluate the performance of the type-1 FLRBC;
    Initialize the parameters [θ_1(t)] of the type-1 FLRBC;
    Evaluate the non-adaptive classifier error rate e_1(t) corresponding to
      θ_1(t) by using the testing prototypes;
    // Keep training and testing until the parameters have been trained/tested for 1000 epochs
      or there have been no improvements for 200 epochs;
    Set the counter of training epochs, Counter_epoch, to be 0;
```

```
Set the counter of no improvements, Counter_{no improvements}, to be 0;
While ( Counter_{epoch} < 1000 and Counter_{no improvements} < 200 )
  { Let Counter_{epoch} = Counter_{epoch}+1;
    Train the parameters of the type-1 FLRBC by using the training
      prototypes, and let the resulting parameters be θ_{temp};
    Evaluate the non-adaptive classification error rate e_{temp} corresponding
      to θ_{temp};
    If ( e_{temp} < e_1(t) )
      { Set θ_1(t) to be θ_{temp};
        Set e_1(t) to be e_{temp}; }
    Else
      { Let Counter_{no improvements} = Counter_{no improvements}+1; }
  }
Evaluate the adaptive classification error rate e_1^a(t) corresponding to θ_1(t);
// Train the parameters and evaluate the performance of the interval type-2 FLRBC;
Initialize the parameters [θ_2(t)] of the interval type-2 FLRBC based on the
  optimal parameters of the type-1 FLRBC θ_1(t);
Evaluate the non-adaptive classifier error rate e_2(t) corresponding to θ_2(t)
  by using the testing prototypes;
// Keep training and testing until the parameters have been trained/tested for 1000 epochs
  or there have been no improvements for 200 epochs;
Set the counter of training epochs, Counter_{epoch}, to be 0;
Set the counter of no improvements, Counter_{no improvements}, to be 0;
While ( Counter_{epoch} < 1000 and Counter_{no improvements} < 200 )
  { Let Counter_{epoch} = Counter_{epoch}+1;
    Train the parameters of the interval type-2 FLRBC by using the training
      prototypes, and let the resulting parameters be θ_{temp};
```

```
        Evaluate the non-adaptive classification error rate e_temp corresponding
          to θ_temp;
        If ( e_temp < e_2(t) )
          { Set θ_2(t) to be θ_temp;
            Set e_2(t) to be e_temp; }
        Else
          { Let Counter_no improvements = Counter_no improvements+1; }
      }
    Evaluate the adaptive classification error rate e_2^a(t) corresponding to θ_2(t);
  }
Compute the mean and standard deviation of e_B(t), e_B^a(t), e_1(t), e_1^a(t), e_2(t)
  and e_2^a(t) over t = 1,...,200.
```

The experimental results, i.e., the mean and standard deviation of $e_B(t)$, $e_B^a(t)$, $e_1(t)$, $e_1^a(t)$, $e_2(t)$ and $e_2^a(t)$ over the 200 designs, are summarized in Table 5.3.

Observe from Tables 5.1 and 5.3 that:

- For each classifier, the adaptive mode has a smaller average classification error rate, but a slightly larger standard deviation of classification error rate, than the non-adaptive mode.

- Both the type-1 and interval type-2 FLRBCs have better performance than the Bayesian classifier, and the interval type-2 FLRBC has better performance than the type-1 FLRBC, where by *better* we mean smaller average and standard deviation of classification error rates over the 200 designs for both the non-adaptive and adaptive modes.

- For the non-adaptive working mode, each classifier has similar statistics (i.e., mean and standard deviation of classification error rates) for both the 200 designs (Table 5.3) and the 869 designs (Table 5.1), which means that the experimental results over the 200 random designs are already enough and we do not have to enumerate all possible designs to evaluate the performance of a classifier.

5.3 Blind Test

In the first year of our study, for the binary classification of tracked versus wheeled vehicles, we applied the interval type-2 FLRBC to the 51 blind data records of the normal terrain, and had 47 and 49 data records correctly classified in the worst and best cases, respectively. In the second year of our study, for the multi-category classification of heavy-tracked, light-tracked, heavy-wheeled and light-wheeled vehicles, we applied the Bayesian classifier and interval type-2 FLRBCs to the 51 blind data records of the normal terrain, and had 51% and 76% classification accuracy rates for the Bayesian classifier, and 78% and 92% classification accuracy rates for the FLRBCs, in the worst and best cases, respectively.

This year we applied the Bayesian classifier, type-1 and interval type-2 FLRBCs designed for the multi-category classification of ground vehicles based on the acoustic data of multiple-terrains to the 71 blind data records of multiple-terrains. In this section we describe our blind testing experiments.

Classifier Designs: For each classifier, we have used the 200 designs that were obtained during the experiment of Section 5.2. To investigate the impact of the number of classifier designs (local experts) on spatio-temporal decision fusion, we chose the best 50, 100, 150, and 200 designs out of all available 200 designs of each classifier, respectively, to obtain the overall decision. By *best* we mean the classifier designs having smallest non-adaptive classification error rates among the 200 classifier designs obtained in the experiment of Section 5.2.

Data Blocks (Prototypes): From each blind data record we generated 80 CPA-based data blocks, assuming that the information of CPA is available and the fundamental frequency is in the range $[8, 20]$ Hz. To investigate the impact of the number of data blocks (observations) on spatio-temporal decison fusion, we have used the first 20, 40, 60, and 80 data blocks out of all available 80 CPA-based data blocks of each blind run, respectively, to obtain the overall decision.

Spatio-Temporal Decision Fusion: Each classifier (Bayesian, type-1 or interval type-2) only needs to make one decision for each blind data record, even though we have multiple data blocks for the record and multiple designs of the classifier. So, we have used the spatio-temporal decision fusion based on majority voting techniques. More specifically, given a classifier and a blind data record, we have treated all decisions provided by the m designs of the classifier for the n data blocks of the record as independent local decisions, and have cast a majority vote by using the mn local decisions to reach a final decision, i.e, the blind record is classified as a heavy-tracked (light-tracked, heavy-wheeled or light-wheeled) vehicle if and only if more than $mn/2$ local decisions are heavy-tracked (light-tracked, heavy-wheeled or light-wheeled).

Classification designs for the 71 blind data records by using different number of classifier designs and different number of data blocks are summarized in Tables 5.5-5.20, as indexed in Table 5.4.

Table 5.1: Average and standard deviation (SD) of the testing errors over the 869 designs for the experiment of leaving out one run from each terrain.

Classifier	**Mean**	**STD**
Bayesian [$e_B(t)$]	20.7617%	0.1076
Type-1 FLRBC [$e_1(t)$]	12.8193%	0.0723
Interval Type-2 FLRBC [$e_2(t)$]	9.2193%	0.0552

Table 5.2: Average and standard deviation (SD) of the testing errors across the 89 designs of the leave-one-run-out experiment (Table 8.1 of [5]).

Classifier	**Average**	**SD**
Bayesian	27.8652%	0.262109
Type-1 Non-hierarchical	6.9522%	0.080791
Interval Type-2 Non-hierarchical	3.1882%	0.045050
Type-1 Hierarchical FLRBC in Parallel	5.2809%	0.052593
Interval Type-2 Hierarchical FLRBC in Parallel	4.9345%	0.053848
Type-1 Hierarchical FLRBC in Series	3.8343%	0.046575
Interval Type-2 Hierarchical FLRBC in Series	3.2351%	0.040956

Table 5.3: Mean and standard deviation (STD) of the classification error rates over the 200 designs for the experiment of non-adaptive and adaptive working modes.

	Non-Adaptive		**Adaptive**	
Classifier	**Mean**	**STD**	**Mean**	**STD**
Bayesian [$e_B(t)$ and $e_B^a(t)$]	20.7469%	0.09945	14.1219%	0.1448
Type-1 FLRBC [$e_1(t)$ and $e_1^a(t)$]	12.8312%	0.0728	5.6859%	0.0822
Interval Type-2 FLRBC [$e_2(t)$ and $e_2^a(t)$]	9.1250%	0.0544	3.1453%	0.0591

Table 5.4: Correspondance of the blind testing result tables to the number of classifier designs and the number of data blocks used.

Number of	Number of Data Blocks Used			
Classifier Designs Used	20	40	60	80
50	Table 5.5	Table 5.6	Table 5.7	Table 5.8
100	Table 5.9	Table 5.10	Table 5.11	Table 5.12
150	Table 5.13	Table 5.14	Table 5.15	Table 5.16
200	Table 5.17	Table 5.18	Table 5.19	Table 5.20

Table 5.5: Blind testing results by using the 20 data blocks of each blind run and the 50 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Undetermined	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.5: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.5: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Wheeled
F103.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F104.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F109.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F120.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.5: continued ...

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled

Table 5.6: Blind testing results by using the 40 data blocks of each blind run and the 50 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.6: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.6: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Undetermined	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.6: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled

Table 5.7: Blind testing results by using the 60 data blocks of each blind run and the 50 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.7: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.7: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Tracked
F111.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Light-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.7: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.8: Blind testing results by using the 80 data blocks of each blind run and the 50 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.8: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.8: continued ...

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F111.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.8: continued ...

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.9: Blind testing results by using the 20 data blocks of each blind run and the 100 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.9: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.9: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F104.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F109.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F120.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.9: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled

Table 5.10: Blind testing results by using the 40 data blocks of each blind run and the 100 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.10: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.10: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.10: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.11: Blind testing results by using the 60 data blocks of each blind run and the 100 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.11: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.11: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Tracked
F111.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Light-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.11: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.12: Blind testing results by using the 80 data blocks of each blind run and the 100 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.12: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.12: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F111.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.12: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.13: Blind testing results by using the 20 data blocks of each blind run and the 150 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.13: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.13: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F104.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F109.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F120.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.13: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled

Table 5.14: Blind testing results by using the 40 data blocks of each blind run and the 150 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.14: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.14: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.14: continued ...

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.15: Blind testing results by using the 60 data blocks of each blind run and the 150 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.15: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.15: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Tracked
F111.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Light-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.15: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.16: Blind testing results by using the 80 data blocks of each blind run and the 150 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.16: continued ...

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.16: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F111.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.16: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.17: Blind testing results by using the 20 data blocks of each blind run and the 200 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.17: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.17: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F104.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F109.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F120.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.17: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Wheeled

Table 5.18: Blind testing results by using the 40 data blocks of each blind run and the 200 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.18: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.18: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F111.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.18: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.19: Blind testing results by using the 60 data blocks of each blind run and the 200 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E001.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
E074.fea	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085.fea	Light-Tracked	Light-Tracked	Light-Tracked
E086.fea	Light-Tracked	Light-Tracked	Light-Tracked
E093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.19: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085.fea	Light-Tracked	Light-Tracked	Light-Tracked
F086.fea	Light-Tracked	Light-Tracked	Light-Tracked
F087.fea	Light-Tracked	Light-Tracked	Light-Tracked
F088.fea	Light-Tracked	Light-Tracked	Light-Tracked
F093.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.19: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F101.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110.fea	Heavy-Tracked	Heavy-Wheeled	Heavy-Tracked
F111.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117.fea	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118.fea	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119.fea	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120.fea	Light-Wheeled	Heavy-Wheeled	Light-Wheeled
F173.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.19: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199.fea	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200.fea	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Table 5.20: Blind testing results by using the 80 data blocks of each blind run and the 200 designs of the Bayesian classifier, type-1 and interval type-2 FLRBCs.

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
E001	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E002	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E019	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E020	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E045	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E046	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E057	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E058	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E073	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E074	Heavy-Tracked	Heavy-Tracked	Light-Tracked
E085	Light-Tracked	Light-Tracked	Light-Tracked
E086	Light-Tracked	Light-Tracked	Light-Tracked
E093	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E094	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E097	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E098	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
E173	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E174	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
E177	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.20: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
E178	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F005	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F006	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F007	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F008	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F010	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F019	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F020	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F021	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F022	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F077	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F078	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F079	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F080	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F085	Light-Tracked	Light-Tracked	Light-Tracked
F086	Light-Tracked	Light-Tracked	Light-Tracked
F087	Light-Tracked	Light-Tracked	Light-Tracked
F088	Light-Tracked	Light-Tracked	Light-Tracked
F093	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F094	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F095	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F096	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled

continued...

Table 5.20: continued ...

Blind File	**Bayesian Classifier**	**Type-1 FLRBC**	**Interval Type-2 FLRBC**
F101	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F102	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F103	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F104	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F109	Light-Wheeled	Light-Wheeled	Light-Wheeled
F110	Heavy-Tracked	Heavy-Wheeled	Heavy-Wheeled
F111	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F112	Light-Wheeled	Light-Wheeled	Light-Wheeled
F117	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F118	Light-Wheeled	Light-Wheeled	Light-Wheeled
F119	Heavy-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F120	Light-Wheeled	Heavy-Wheeled	Heavy-Wheeled
F173	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F174	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F175	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F176	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F181	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F182	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F183	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F184	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F185	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F186	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked

continued...

Table 5.20: continued ...

Blind File	Bayesian Classifier	Type-1 FLRBC	Interval Type-2 FLRBC
F187	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F188	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F189	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F190	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F197	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F198	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked
F199	Heavy-Tracked	Heavy-Tracked	Heavy-Tracked
F200	Heavy-Wheeled	Heavy-Tracked	Heavy-Tracked

Chapter 6

Conclusions

In this report we have summarized our studies conducted from July 2003 to July 2004 for the multi-category classification of ground vehicles based on the acoustic data of multiple-terrains.

Data pre-processing (including elimination of redundant records, processing of data distortion, and generation of prototypes), feature extraction, and uncertainty analysis were performed before designing classifiers.

- We observed that there are obvious distortions in some records; hence, we performed distortion processing as part of data pre-processing.
- We assumed that the fundamental frequency is in the range of $[8, 20]$ Hz for all terrains during the feature extraction.
- For each kind of vehicle, we observed that its acoustic features have different distributions across different terrains; hence, for each kind of vehicle, we used distinct fuzzy sets to model its features and established one distinct fuzzy logic rule on each different terrain.

We established the Bayesian classifier, and type-1 and interval type-2 FLRBCs. These classifiers have similar architectures, consisting of four sub-systems one for each terrain, and having one probability model (Bayesian classifier) or fuzzy logic rule (type-1 and interval type-2 FLRBCs) for each kind of vehicle on each terrain. They are different in the way that this common architecture is implemented. The Bayesian classifier was established based on our assumptions about the probability distributions of the acoustic features and the Bayesian inference mechanisms. The type-1 and interval type-2 FLRBCs were established based on our fuzzy set models for the acoustic features and theories of fuzzy logic systems.

Given a set of training data, the parameters of the Bayesian classifier were estimated by using the maximum likelihood estimation method; and, the parameters of the type-1 and interval type-2 FLRBCs were optimized by using the steepest descent algorithm.

We conducted the experiment of leaving out one run from each terrain to design and evaluate the performance of the Bayesian classifier, type-1 and interval type-2 FLRBCs. We observed through that experiment that:

- For the non-adaptive working mode, both the type-1 and interval type-2 FLRBCs have significantly better performance (smaller mean and standard deviation of the classification error rate) than the Bayesian classifier, and the interval type-2 FLRBC has better performance than the type-1 FLRBC.

- Comparing the non-adaptive and adaptive working modes, each classifier has a significantly smaller average but a slightly larger standard deviation of classification error rates in the adaptive mode than in the non-adaptive mode.

- For the adaptive working mode, both the type-1 and interval type-2 FLRBCs have significantly better performance than the Bayesian classifier, and the interval type-2 FLRBC has better performance than the type-1 FLRBC.

We applied the Bayesian classifier, type-1 and interval type-2 FLRBCs obtained from the experiment of leaving out one run from each terrain to the 71 blind data records of all terrains, and used spatio-temporal decision fusion to obtain one overall decision for each blind data record.

With this report, we have completed our study into the *classification of ground vehicles based on their acoustic emissions by using fuzzy logic rule based classifiers.* Our overall conclusion from this study is that fuzzy logic rule based classifiers always outperform a Bayesian classifier, and look quite promising for real-time applications.

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