Trabajo

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1 Introduction

This paper consists of all works I am doing for my PH.D in Music Information Retrieval. I will update this paper with new works and experiments, and the results and conclusion of theses experiments.

2 New database for bass and melody classification

A new database of MIDI files has been created for classical, jazz and popular genres: class, jazz and kar. Each database has been divided in two datasets: train and test.

Train datasets will be used to train classifiers and contains about 66% of all MIDI files from databases.

Table 1 shows the number of MIDI files in each dataset.

All tracks in MIDI files have been tagged as bass, melody or accompaniment. Percussion tracks are considered as not valid and have not been tagged. A constraint is set that melody and bass lines must be in different tracks. All tracks that have not been tagged as bass or melody have been tagged as accompaniment.

Table 2 shows the number of bass, melody and accompaniments tracks for each MIDI dataset.

	Number of MIDI files		
Dataset	Complete dataset	Train	Test
class	984	647	337
jazz	1289	858	431
kar	1347	899	448

Table 1: Number of MIDI files in each dataset

Datasets	bass tracks		melody tracks		accomp tracks		total tracks
class	1036	-16.87%	1669	-27.18%	3436	-55.95%	6141
jazz	1327	-20.01%	1792	-27.02%	3513	-52.97%	6632
kar	1382	-12.16%	1430	-12.58%	8555	-75.26%	11367
class_train	677	-16.98%	1069	-26.81%	2241	-56.21%	3987
jazz_train	886	-21.23%	1135	-27.19%	2153	-51.58%	4174
kar_train	928	-12.11%	955	-12.46%	5781	-75.43%	7664
class_test	359	-16.67%	600	-27.86%	1195	-55.48%	2154
jazz_test	441	-17.94%	657	-26.73%	1360	-55.33%	2458
kar_test	454	-12.26%	475	-12.83%	2774	-74.91%	3703

Table 2: Tracks tagged for each dataset

3 Repetición de los experimentos del artículo del ICPRAM

Se repiten los experimentos realizados en [3]. En este caso se han utilizado las bases de datos class_train, jazz_train y kar_train en lugar de clas200, jaz200 y kar200.

Definición de FP, FN y TP según [3]:

FP is the number of false-positives (the classifier selects a non-bass track), TP is the number of true-positives (the selected track contains the correct bass line), and FN is the number of false-negatives (the classifier does not select any track but the MIDI file indeed contains at least one bass track). The selection is considered as successful both if the selected track contains the correct bass line or the MIDI file has not any bass track and the classifier does not select any bass track (a true-negative situation).

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Precision = \frac{TP}{TP + FN} \tag{2}$$

$$F - measure = \frac{Recall x Precision}{Recall + Precision} \tag{3}$$

Definición de errores Tipo 1, Tipo 2 y Tipo 3 [1]:

$$\begin{aligned} FP = Tipo1 + Tipo2 \\ FN = Tipo3 \end{aligned} \tag{4}$$

	Number of different tags
All tags obtained	3971
Bass tags obtained	451

Table 3: Number of different tags related to bass and non bass content

Bass tag	Number of repetitions
basse 2	19
bass	25
1b	25
2b	33
bajo	34
bass (bb)	35
basse 2	41
bass	46
basse	83
b	136
bass	405
bass (bb)	612

Table 4: Number of different tags related to bass and non bass content

	kar	class	jazz
No bass tracks	24	91	3
One bass track	825	450	829
> one bass track	50	106	26

Table 5: MIDI files classified by the number of bass tracks

Dataset	Bass tracks	Non bass tracks	Total
class	678 (17.00%)	3309 (83.00%)	3987
jazz	886 (21.23%)	3288 (78.77%)	4174
kar	928 (12.11%)	6736 (87.89%)	7664

Table 6: Number of bass and non-bass tracks in the MIDI datasets. Proportions of both kind of tracks per genre are also shown

Dataset	Bass Success (std dev)	Melody Success (std dev)
class_train	95.57% (0.95)	87.11% (1.54)
jazz_train	99.42% (0.37)	93.84% (1.22)
kar_train	99.21% (0.30)	96.14% (0.69)
All	98.36% (0.30)	92.31% (0.60)

Table 7: Bass versus non-bass classification and melody versus non-melody classification.

	Dataset	Acc. %	Prec	Rec	F-m
Bass track selection	class_train.csv	86.24%	0.87	0.98	0.92
	jazz_train.csv	99.18%	0.99	1.00	1.00
	kar_train.csv	97.66%	0.98	1.00	0.99
Melody track selection	class_train.csv	84.70%	0.85	0.99	0.92
	jazz_train.csv	94.87%	0.95	0.99	0.97
	kar_train.csv	87.32%	0.94	0.92	0.93

Table 8: Bass Track Selection.

3.1 Dictionary-Based Tagging (Section 5 in [1])

3.2 Bass versus Non-bass Classification (Section 6.1)

Clasificación de las pistas como "bajo" o "no bajo" utilizando el algoritmo RF con cross-validation (K=10 F=6). Se utilizan las bases de datos class_train, jazz_train y kar_train tanto para bajo como para melodía. La base de datos All contiene las tres bases de datos train.

Results are shown in table 7.

3.3 Bass Track Selection (Section 6.2)

Selección de la pista de bajo con $\theta = 0.25$. $P(B|i) > |theta$.

También se ha realizado la selección de la pista de melodía utilizando la nueva base de datos para compararlo con los resultados mostrados en el paper del ICPRAM [3], que son los obtenidos en la Tesis de Pierre [1]. Los resultados se muestran en la tabla 8

3.4 Bass Track Selection across Genres (Section 6.3)

Los conjuntos de entrenamiento jazz_kar, class_kar y class_jazz se han construído utilizando las bases de datos de training jazz_train, kar_train y class_train. El experimento se repite con el umbral $\theta = 0.25$.

Se ha repetido la selección de la pista que contiene la melodía para compararlo con los resultados mostrados en el paper del ICPRAM [3], que son los obtenidos en la Tesis de Pierre [1]. Los resultados se muestran en la tabla 9.

	Dataset	Acc. %	Prec	Rec	F-m
Bass	class_train.csv	86.24%	0.87	0.98	0.92
track	jazz_train.csv	99.18%	0.99	1.00	1.00
track	kar_train.csv	97.66%	0.98	1.00	0.99
Melody	class_train.csv	84.70%	0.85	0.99	0.92
track	jazz_train.csv	94.87%	0.95	0.99	0.97
selection	kar_train.csv	87.32%	0.94	0.92	0.93

Table 9: Bass Track Selection across Genres

	Set	Acc%	Prec.	Recall	F-m
Bass track selection	class_train	86.40%	0.87	0.98	0.92
using melody information	jazz_train	99.18%	0.99	1	1
	kar_train	97.78%	0.98	1	0.99
Bass track selection	class_train.csv	86.24%	0.87	0.98	0.92
without melody	jazz_train.csv	99.18%	0.99	1	1
information	kar_train.csv	97.66%	0.98	1	0.99

Table 10: Bass track selection using melody information.

3.5 Interaction Between Melody and Bass Track Selection

We have detected a problem to select the bass track using the melody information. The problem rises when a MIDI file has not bass track nor melody track. In this case if the probability of selecting the virtual track 0 for melody $P(t_0|M) = 1$ implies that the probability of selecting t0 as bass is computed as $P(t_0|B)(1 - P(t_0|M) = 1) = 0$. Therefore, if the melody track selected is t_0 (no melody track) then t0 can not be the bass track.

To fix this issue $\hat{i_B}$ has been defined:

$$\hat{i_B} = \arg\max_i \begin{cases} P(i|B), i = 0 \\ P(i|B)(1 - P(i|M))), i \neq 0 \end{cases} \tag{5}$$

3.5.1 Interaction Between Melody and Bass Track Selection (Section 6.4)

In this experiment we have executed again experiments from ICPRAM 2012 (section 6.4) using the new dataset. Results are shown in tables 10 and 11.

3.5.2 Interaction Between Melody and Bass Track Selection With 200 Dataset

This time we have repeated the experiment of bass track selection with the information obtained in melody track selection using the datasets used in paper [3]. For this experiment we have used an schema leave-one-out as it was done

	Set	Acc%	Prec.	Recall	F-m
Melody track selection with bass information	class_train	84.70%	0.85	1	0.92
	jazz_train	94.87%	0.95	0.99	0.97
	kar_train	87.32%	0.94	0.93	0.93
Melody track selection without bass information	class_train.csv	84.70%	0.85	0.99	0.92
	jazz_train.csv	94.87%	0.95	0.99	0.97
	kar_train.csv	87.32%	0.94	0.92	0.93

Table 11: Melody track selection using bass information.

	Set	Acc%	Prec.	Recall	F-m
Bass track selection with melody information	clas200	99.50%	1	0.99	0.99
	jazz200	100.00%	1	1	1
	kar200	93.50%	0.93	1	0.97
Bass track selection without melody information	clas200	99.50%	1	0.99	0.99
	jazz200	100.00%	1	1	1
	kar200	93.50%	0.93	1	0.97

Table 12: Bass track selection in 200 databases using melody information.

in [3] and the same values used in section 6.4. Results are shown in tables 12 and 13.

3.5.3 Interaction Between Melody and Bass Track Selection Using Train and Test Datasets

In this experiment we have selected the bass track with the information obtained in melody track selection but using the dataset class_train, jazz_train and ka_train for training the algorithm and class_test, jazz_test and kar_test for testing.

Results are shown in tables 14 and 15.

	Set	Acc%	Prec.	Recall	F-m
Melody track selection with bass information	clas200	99.50%	0.99	1	1
	jazz200	98.50%	0.99	0.99	0.99
	kar200	77.00%	0.88	0.85	0.87
Melody track selection without bass information	clas200	99.50%	0.99	1	1
	jazz200	98.50%	0.99	0.99	0.99
	kar200	77.50%	0.88	0.86	0.87

Table 13: Melody track selection in 200 databases using bass information.

	Train Set	Test Set	Acc%	Prec.	Recall	F-m
Bass track selection	class_train	class_test	87.24%	0.88	0.99	0.93
with melody information	jazz_train	jazz_test	98.61%	0.99	1	0.99
	kar_train	kar_test	98.21%	0.98	1	0.99
Bass track selection	class_train	class_test	87.24%	0.87	0.99	0.93
without melody information	jazz_train	jazz_test	98.61%	0.99	1	0.99
	kar_train	kar_test	97.99%	0.98	1	0.99

Table 14: Bass track selection with melody information using train and test datasets.

	Train Set	Test Set	Acc%	Prec.	Recall	F-m
Melody track selection	class_train	class_test	88.72%	0.89	1	0.94
with bass information	jazz_train	jazz_test	88.86%	0.9	0.98	0.94
	kar_train	kar_test	87.05%	0.93	0.93	0.93
Melody track selection	class_train	class_test	88.13%	0.88	1	0.94
without bass information	jazz_train	jazz_test	88.86%	0.9	0.98	0.94
	kar_train	kar_test	87.28%	0.93	0.93	0.93

Table 15: Melody track selection with bass information using train and test datasets.

3.5.4 Conclusions

In section 3.5.1 we expected an improvement in bass track selection using melody information a priory (and melody track selection using bass information). However results in are not better, and in some cases worse, using information a priory.

Higher differences have been detected in class_train database, therefore we have analyzed the differences in bass and melody track selection for this database.

Table 16shows all MIDI files from class_train database were bass track was properly classified without the melody information but failed using melody information a priory.

In the three cases the bass track has the higher probability of bass, but they also have an high probability of melody. Then the probability P(i—B)(1-P(i—M)) is penalized. If the number of bass tracks with an high value of melody probability P(M—i) is high the bass-track selection using the described method in this section will not improve the results.

Table 17 shown an histogram with the probability $P(M|i)$ of bass tracks, and $P(B|i)$ of melody tracks in class_train database.

Midi file	track	$p(M\|t)$	$p(B\|t)$	$p(A\|t)$	tag	$p(i\|B)(1-p(i\|M))$
Renaissance_Renaissance-Late_	0					0.38
Victoria_Quam_Pulchri_Sunt-	1	0.5	0.0	0.7	melody	0.0
2-Gloria-c.mid	2	0.0	0.0	0.9	melody	0.0
	3	0.0	0.0	0.8	accomp	0.0
	4	0.6	0.4	0.0	bass	0.34
Medieval_ArsNova_	0					0.15
Machau_machaut-b17.mid	2	1.0	0.0	0.0	melody	0.0
	3	0.1	0.7	0.4	accomp	0.39
	4	0.15	0.7	0.3	bass	0.38
Renaissance_Renaissance-Late_	0					0.45
Victoria_Quicumque_	1	0.0	0.0	1.0	melody	0.0
Christum_Quaeritis-s.mid	2	0.15	0.0	0.7	accomp	0.0
	3	0.0	0.0	1.0	accomp	0.0
	4	0.7	0.3	0.0	bass	0.19

Table 16: Probabilities for MIDI files were bass track was select wrongly using melody information.

$P(M\|t)$	Num. of bass tracks
0.0	515
0.1	102
0.2	32
0.3	13
0.4	5
0.5	3
0.6	1
0.7	3
0.8	2
0.9	0
1.0	1

$P(B\|t)$	Num. of melody tracks
0.0	1014
0.1	19
0.2	5
0.3	2
0.4	3
0.5	0
0.6	3
0.7	1
0.8	4
0.9	7
1.0	11

Table 17: Probabilities histograms for bass and melody tracks.

3.6 Interaction Between Melody, Bass and Accompaniment Track Selection

All tracks in database are tagged as bass, melody and accompaniment. How can we improve the bass and melody tracks detection using the information of accompaniments tracks?

For this purpose we have proposed two methods. The first one consists in use the probability $p(A|t)$ of accompaniment tracks in the same way that we did in the section 2.5.

In the second method a new classifier will be implemented using the probabilities $p(B|t)$, $p(M|t)$ and $p(A|t)$ of each track as attributes to train the classifier.

3.6.1 Bass Track Selection Using Information A Priori of Melody and Accompaniment

In section 3.5 the bass track selected for a midi file is:

$$\hat{i_B} = \arg\max_i \{p(i|M, \hat{i_B} \neq i)\} \tag{6}$$

Adding the accompaniment information to the probabilities of bass tracks using melody information we obtain:

$$\begin{aligned} p(i|B, \hat{i_M} \neq i) &= p(i|B)(1 - p(i|M)) \\ p(i|B, \hat{i_M} \neq i, \hat{i_A} \neq i) &= p(i|B, \hat{i_M} \neq i)(1 - p(i|A)) \\ p(i|M, \hat{i_M} \neq i, \hat{i_A} \neq i) &= p(i|B)(1 - p(i|M))(1 - p(i|A)) \end{aligned} \tag{7}$$

The track for bass line selected is:

$$\hat{i_B} = \arg\max_i \{p(i|B)(1 - p(i|M))(1 - p(i|A))\} \tag{8}$$

And of course it could be used to for the melody track selection:

$$\hat{i_M} = \arg\max_i \{p(i|M)(1 - p(i|B))(1 - p(i|A))\} \tag{9}$$

The experiments have been performed on class-train, jazz-train and kar-train databases using the leave-one-out schema. RF algorithm has been used to obtain the probabilities. Results are shown in the tables 18 and 19:

3.6.2 A Second Classifier Trained using Bass, Melody and Accompaniment Probabilities

In the previous experiments we have obtained the probabilities $p(B|t)$, $p(M|t)$ and $p(A|t)$ for each track in databases.

In the scope of bass track selection exists the possibility that none of the track of a MIDI file contains the bass line. In this way a virtual zero track has been added with $p(B|t) = \theta$ and probabilities $p(i|B)$ has been computed. This

	Set	Acc%	Prec.	Recall	F-m
Bass track selection	class_train	87.48%	0.89	0.97	0.93
using melody and	jazz_train	99.42%	0.99	1.00	1.00
accomp information	kar_train	97.89%	0.99	0.99	0.99
Bass track selection	class_train	86.24%	0.87	0.98	0.92
without melody and	jazz_train	99.18%	0.99	1.00	1.00
accomp	kar_train	97.66%	0.98	1.00	0.99

Table 18: Bass track selection using melody and accompaniment information.

	Set	Acc%	Prec.	Recall	F-m
Melody track selection	class_train	85.63%	0.86	0.99	0.92
with bass and accomp	jazz_train	93.94%	0.96	0.98	0.97
information	kar_train	86.87%	0.95	0.91	0.93
Melody track selection	class_train	84.70%	0.85	0.99	0.92
without bass and	jazz_train	94.87%	0.95	0.99	0.97
accomp information	kar_train	87.32%	0.94	0.92	0.93

Table 19: Melody track selection using bass and accompaniment information

Track	$p(i\|M)$	$p(i\|B)$	$p(i\|A)$
0	0.00	0.23	0.00
1	0.48	0.00	0.06
2	0.29	0.00	0.21
3	0.07	0.00	0.59
4	0.03	0.77	0.00

Table 20: Example of the $p(i|B)$, $p(i|M)$ and $p(i|A)$ for a MIDI file.

Dataset		(1) trees.RandomFo	(2) functions.S	(3) bayes.Naive
bass_class	(100)	93.80(0.90) |	93.43(0.89)	92.78(1.13) *
bass_jazz	(100)	99.25(0.38) |	99.37(0.35)	99.45(0.31) v
bass_kar	(100)	99.09(0.30) |	99.12(0.27)	98.45(0.42) *
bass_all	(100)	97.84(0.34) |	97.85(0.32)	97.24(0.33) *
		(v/ /*) |	(0/4/0)	(1/0/3)

Table 21: Bass versus non_bass classification using $p(i|B)$, $p(i|M)$ and $p(i|A)$.

Dataset		(1) trees.RandomFo	(2) functions.S	(3) bayes.Naive
melody_class	(100)	86.15(1.38) |	85.80(1.13)	86.46(1.38)
melody_jazz	(100)	93.41(1.03) |	90.99(1.08) *	72.27(1.85) *
melody_kar	(100)	97.06(0.56) |	96.32(0.55) *	91.05(1.13) *
melody_all	(100)	92.84(0.60) |	91.89(0.48) *	87.41(0.93) *
		(v/ /*) |	(0/1/3)	(0/1/3)

Table 22: Melody versus non_melody classification using $p(i|B)$, $p(i|M)$ and $p(i|A)$.

procedure has also been used for $p(i|M)$ and $p(i|A)$. For threshold θ has been used the value 0.25.

Table 20 shows an example of these features for a midi file

Probabilities $p(i|B)$, $p(i|M)$ and $p(i|A)$ of each track in class_train, jazz_train and kar_train databases have been used as features to create the arff files used to train the classifiers.

In the first experiment RF, SMO and NaiveBayes algorithms have been tested in the context of bass versus non_bass and melody versus non_melody classification.

Results are shown in tables 21 and 22.

In the second experiment the SMO algorithm has been used to select the bass and melody tracks for each MIDI file. We have used the databases class-train, jazz-train and kar-train, and for each database an SMO classifier has been implemented using a leave-one-out schema. Using Weka application the parameters a, b, c and d of the following function are obtained:

$$SMO(i) = a * p(i|M) + b * p(i|B) + c * p(i|A) + d \tag{10}$$

And the bass track selected is

$$\hat{i_B} = \arg\min_i \{SMO(i)\} \tag{11}$$

	Set	Acc%	Prec.	Recall	F-m
Bass track selection using SMO algorithm	class_train	87.33%	0.88	0.98	0.93
	jazz_train	99.30%	0.99	1.00	1.00
	kar_train	97.78%	0.98	1.00	0.99
Bass track selection without melody and accomp	class_train.csv	86.24%	0.87	0.98	0.92
	jazz_train.csv	99.18%	0.99	1.00	1.00
	kar_train.csv	97.66%	0.98	1.00	0.99

Table 23: Bass track selection using SMO second classifier.

	Set	Acc%	Prec.	Recall	F-m
Melody track selection using SMO algorithm	class_train	84.70%	0.85	1.00	0.92
	jazz_train	94.76%	0.95	1.00	0.97
	kar_train	90.10%	0.90	1.00	0.95
Melody track selection without bass and accomp information	class_train.csv	84.70%	0.85	0.99	0.92
	jazz_train.csv	94.87%	0.95	0.99	0.97
	kar_train.csv	87.32%	0.94	0.92	0.93

Table 24: Melody track selection using SMO second classifier.

Results for bass track selection using a second SMO classifier are shown table 23. Experiments have been repetated for melody track selection and results are shown in table 24.

4 Bass Track Selection Considering its Imbalanced Context (preliminary experiments)

Bass and melody track identification can be considered as a problem in imbalances scenarios where the bass or melody track can be considered as the minority class [2]. As shown in table 2.1 the number of bass tracks is much lower that the number of non-bass tracks.

Table 2 shows the number of bass and melody tracks in class, jazz and kar datasets.

The aim of this work is to compare how the bass track selection can be improved in balanced scenarios.

4.1 Over-sampling and sub-sampling filters in Weka

For experiments Resample and SMOTE filters of Weka have been used for over-sampling and SpreadSubsample has been used for sub-samping in the next way:

Resample -B 1.0 -S 1 -Z ¡percentage¿
SMOTE -C 0 -K 5 -P ¡percentage¿ -S 1
SpreadSubsample -M 1.0 -X 0.0 -S 1

Type of track	Dataset	Resample	SMOTE
Bass	class	166.26	392.76
	jazz	159.98	299.77
	kar	175.5	622.50
Melody	class	145.64	167.94
	jazz	145.96	170.09
	kar	174.84	594.90
Accomp	class	111.90	27.02
	jazz	105.94	12.63
	kar	150.52	204.23
Bass	class_train	166.04	388.92
	jazz_train	157.55	271.11
	kar_train	175.78	625.86
Melody	class_train	146.38	172.97
	jazz_train	145.62	167.75
	kar_train	175.08	602.51
Accomp	class_train	112.42	28.35
	jazz_train	103.16	6.53
	kar_train	150.86	207.01

Table 25: Percentage parameter used in Resample and SMOTE filters.

4.2 Bass versus Non-bass Classification Using Balanced Datasets

For this experiments we have used the datasets class, jazz and kar. Experiment has been performed with Experimenter tool of Weka.

Experimenter has been configured with option "Train/Test Percentage Split (data randomized)" were 66.0% of instances for each dataset has been used for training and has been executed 10 iteration for each dataset classification and each filter.

Table 25 shows the percentage parameter used in Resample and SMOTE filters for each dataset and track type.

Results of bass, melody and accompaniment classifications are shown in table 26.

Bass and melody success in classification is not improved using filters to balance the number of instances. However the rate of true-positives bass and melody tracks classification has been improved. This is due to the increase of the number of false-positives.

The more significative change is in class database. Success and TP rate are shown in following charts.

4.3 Bass track selection

In this experiment we have used training datasets for train classifier and test dataset to verify the results. For each filter it has been created an arff training

		Bass		Melody		Accomp	
Dataset	Filter	Acc (std dev)	TPrate	Acc (std dev)	TPrate	Acc (std dev)	TPrate
class	No filter	95.68% (0.36)	0.88	87.38% (0.54	0.75	84.59% (0.67)	0.90
	Resample	95.41% (0.56)	0.92	85.57% (0.65)	0.80	84.31% (0.73)	0.89
	SMOTE	94.88% (0.45)	0.92	85.31% (0.62)	0.80	84.61% (0.69)	0.89
	*SSS**	93.52% (0.71)	0.96	82.27% (0.64)	0.84	84.42% (0.39)	0.88
jazz	No filter	99.44% (0.10)	0.99	92.86% (0.46)	0.87	92.27% (0.46)	0.95
	Resample	99.30% (0.12)	0.99	92.09% (0.71)	0.92	91.88% (0.49)	0.94
	SMOTE	99.31% (0.09)	0.99	92.41% (0.67)	0.92	92.74% (0.55)	0.94
	*SSS**	99.14% (0.25)	0.99	90.13% (0.53)	0.94	92.45% (0.59)	0.94
kar	No filter	99.35% (0.15)	0.98	96.16% (0.14)	0.82	95.28% (0.25)	0.98
	Resample	99.20% (0.16)	0.98	95.67% (0.32)	0.88	95.21% (0.21)	0.97
	SMOTE	99.15% (0.18)	0.98	94.97% (0.30)	0.90	95.25% (0.18)	0.97
	*SSS**	98.12% (0.47)	0.99	91.50% (0.37)	0.94	94.30% (0.40)	0.95

Table 26: Bass, melody and accompaniment classifications. SSS*: SpreadSub-Sample filter.

Train dataset	Test dataset	Filter	Acc.%	Precision	Recall	F-measure
class_train	class_test	No filter	87.83%	0.88	0.99	0.93
		Resample	87.24%	0.87	1.00	0.93
		SMOTE	88.72%	0.88	1.00	0.94
		SSS	84.87%	0.84	1.00	0.92
jazz_train	jazz_test	No filter	98.61%	0.99	1.00	0.99
		Resample	97.91%	0.98	1.00	0.99
		SMOTE	98.61%	0.99	1.00	0.99
		SSS	98.14%	0.98	1.00	0.99
kar_train	kar_test	No filter	97.99%	0.98	1.00	0.99
		Resample	98.21%	0.98	1.00	0.99
		SMOTE	97.77%	0.98	1.00	0.99
		SSS	96.21%	0.96	1.00	0.98

Table 27: Bass track selection using filters to solve the problem of Unbalanced Contexts.

training file for each training dataset using the parameters from table 3.1 for train datasets.

Results for bass track selection are shown in table **??**.

The same experiment has been repeated in the context of melody track selection and results are shown in table 28

Train dataset	Test dataset	Train Filename	Acc.%	Precision	Recall	F-measure
class_train	class_test	No filter	88.72%	0.89	1.00	0.94
		Resample	87.54%	0.88	1.00	0.93
		SMOTE	85.76%	0.86	1.00	0.92
		SSS	85.16%	0.85	1.00	0.92
jazz_train	jazz_test	No filter	88.86%	0.90	0.98	0.94
		Resample	86.54%	0.87	0.99	0.93
		SMOTE	87.24%	0.88	0.98	0.93
		SSS	87.01%	0.88	0.99	0.93
kar_train	kar_test	No filter	87.28%	0.93	0.93	0.93
		Resample	90.62%	0.93	0.97	0.95
		SMOTE	90.18%	0.92	0.98	0.95
		SSS	89.06%	0.89	1.00	0.94

Table 28: Melody track selection using filters to solve the problem of Unbalanced Contexts.

References

[1] PJ Ponce de León. *A statistical pattern recognition approach to symbolic music classification.* PhD thesis, PhD thesis, Alicante, Spain, 2011.

[2] Raúl Martín, Ramón A Mollineda, and Vicente García. Melodic track identification in midi files considering the imbalanced context. In *Pattern Recognition and Image Analysis*, pages 489–496. Springer, 2009.

[3] Octavio Vicente and José Manuel Iñesta Quereda. Bass track selection in midi files and multimodal implications to melody. In *ICPRAM (1)*, pages 449–458, 2012.