tion feature, which was made up of a vector of 128 on/off values, one for each General MIDI patch. This feature had one network dedicated to it.

These features in particular were selected because they were easy to implement and give a general description of recordings without being optimized to the particular genre taxonomy that was used. Although there is no doubt that twenty better features could be devised, these particular features were chosen simply to show that even non-optimal features could still perform well.

Feature	Explanation					
Orchestration	Which of the 128 MIDI instruments are played					
Number of	Total number of instruments played					
instruments	•					
Percussion	Fraction of note-ons belonging to unpitched					
prevalence	instruments					
Dominant pitch	Fraction of note-ons corresponding to the most					
prevalence	common pitch					
Dominant pitch	Fraction of note-ons corresponding to the most					
class prevalence	common pitch class					
Dominant interval	Number of semi-tones between the two most					
	common pitch classes					
Adjacent fifths	Number of consecutive pitch classes separated					
	by perfect 5ths that represent at least 9% of the					
	notes					
Pitch class variety	Number of pitch classes that represent at least					
(common)	9% of the notes					
Pitch class variety	Number of pitch classes played at least once					
(rare)						
Register variety	Number of pitches played at least once					
Range	Difference between highest and lowest pitches					
Pitchbend fraction	Number of pitch bends divided by total num-					
	ber of note-ons					
Dominant	Magnitude of the highest periodicity bin					
periodicity						
Second dominant	Magnitude of the second highest periodicity					
periodicity	bin					
Combined domi-	Combined magnitude of the two highest perio-					
nant periodicities	dicity bins					
Dominant	Ratio of the frequencies of the two highest					
periodicity	periodicity bins					
strength ratio						
Dominant	Ratio of the periodicities of the two highest					
periodicity ratio	periodicity bins					
Number of strong	Number of periodicity bins with normalized					
periodicities	magnitude > 0.1					
Number of moder-	Number of periodicity bins with normalized					
ate periodicities	magnitude > 0.01					
Number relatively	Number of periodicity bins with frequencies at					
high periodicities	least 25% as high as the highest magnitude					

Table 1: Features extracted from MIDI files and fed into neural networks.

4 Details of the Experiment

The training and testing data consisted of 225 MIDI files hand classified hierarchically into three parent genres (Classical, Jazz and Pop) and nine sub-genres (Baroque, Romantic, Modern Classical, Swing, Funky Jazz, Cool Jazz, Rap, Country and Punk). The particular files that were chosen were selected so as to represent each cate-

gory as broadly as possible (e.g. the Baroque category included operas, violin concertos, harpsichord sonatas, etc., not just organ fugues, for example). This significantly increased the difficulty of the task, as each subgenre only had 20 training recordings (five recordings were reserved for testing in each run) to learn a broad range of music. This was done in order to truly test the viability of the system and its features.

The recordings were classified using an array of eight feed-forward neural networks that consisted of four networks for identifying parent genres and four networks for identifying suő-genres. Each network had a single hidden layer. This division into two groups made it possible to classify parent genres independently from sub-genres.

The input units of each network took in different groups of features (orchestration, pitch statistics, rhythm statistics or stylistic), thus making it possible to study the relative success of the different features in classifying the test data. This made it possible to compare how well different feature groups performed.

A coordination system considered the certainty score output by the networks for each sub-genre in combination with the certainty for each parent genre, and produced a final classification using weighted averages.

This particular classification system was used because it allowed the independent comparison of different groups of features as well as a comparison of how well parent genres were classified relative to sub-genres.

5 Results

A five-fold cross-validation was used to test the performance of the system. The results are shown below:

	Set 1	Set 2	Set 3	Set 4	Set 5	Average
Classical	93	80	100	93	100	93.2
Jazz	73	80	60	53	40	61.2
Pop	100	100	100	100	100	100.0
Average	88.7	86.7	86.7	82.0	80.0	84.8

Table 2: Classification success rates (in percentages) for parent genres for all five cross-validation testing runs.

Set 1 80 0	Set 2 40	Set 3	Set 4 80	Set 5	Average
80		80	80	00	
0			00	80	72.0
	40	0	20	40	20.0
100	40	100	40	80	72.0
40	80	20	40	20	40.0
60	40	60	40	0	40.0
40	20	20	20	0	20.0
80	60	80	60	20	60.0
80	100	100	100	100	96.0
100	100	100	100	100	100.0
64.4	57.8	62.2	55.6	48.9	57.8
	40 60 40 80 80 100	40 80 60 40 40 20 80 60 80 100 100 100	40 80 20 60 40 60 40 20 20 80 60 80 80 100 100 100 100 100	40 80 20 40 60 40 60 40 40 20 20 20 80 60 80 60 80 100 100 100 100 100 100 100	40 80 20 40 20 60 40 60 40 0 40 20 20 20 0 80 60 80 60 20 80 100 100 100 100 100 100 100 100 100

Table 3: Classification success rates (in percentages) for sub-genres for all five cross-validation testing runs.

Overall success rates of 84.8% were achieved for parent genres and 57.8% for sub-genres across all five train-