SOMphony: Visualizing Symphonies using Self Organizing Maps

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Abstract. Symphonies are musical compositions played by a full orchestra which have evolved in style since the 16^{th} Century. Self-Organizing Maps (SOM) are shown to be useful in visualizing symphonies as a musical trajectory across the nodes in a trained map. This allows for some insights about the relationships and influences between and among composers in terms of their composition styles, and how the symphonic compositions have evolved over the years from one major music period to the next. The research focuses on Self Organizing Maps that are trained using 1-second music segments extracted from 45 different symphonies, from 15 different composers, with 3 composers from each of the 5 major musical periods. The trained SOM is further processed by doing a k-means clustering of the node vectors, which then allows for the quantitative comparison of music trajectories between symphonies of the same composer, between symphonies of different composers of the same music period, and between composers from different music periods.

Keywords: Symphony; Self Organizing Maps; k-means clustering; music trajectory.

1 Introduction

Dating back from the 16th Century, a symphony is defined as an elaborate musical composition in about 3 to 5 movements, which is played by a full orchestra. We try to visualize the relationships of the different music periods, from the 16^{th} century Baroque, to the Classical period, into the 19th century, and then the Romantic period, and the early 20th Century, in terms of how the symphonies have evolved. For each period, we choose 3 famous composers and processed 3 of their symphonic compositions, giving a total of 45 symphonies. In particular, we explore the possibility of using Self-Organizing Maps (SOM) [1][2][3][4][5] to encode the musical trajectory of each of the 45 symphonies as a basis for comparing the similarity between symphonic compositions of the same composer, as well as comparisons between compositions by different composers of the same period, and also across music periods. This way, we can, for example, confirm whether great composers, such as Wolfgang Amadeus Mozart, have had lasting influence on music compositions even centuries after his first compositions have been played. This we do by confirming whether indeed the musical trajectories of symphonic compositions from composers after Mozart would still resemble the original Mozart pieces.

In this study, SOM and k-means clustering are used in tandem in order to quantify the trajectory of a symphony from type of music/sound to another, as it progresses through the 3 to 5 movements. Once a trained SOM has been subjected to k-means clustering, we can visualize on a per-second basis the trajectory of each symphonic composition – and this trajectory is the basis for judging whether two symphonies are similar or not. Although we could also have used the U-matrix, we opted to use k-means clustering, as this would allow us to easily tag the nodes and group them [8].

2 Experiment Set-Up

We train Self Organizing Maps using 1-second music segments extracted from 45 different symphonies. These symphonies are from 15 different composers, with 3 composers from each of the 5 major musical periods, and 3 symphonies per composer. The trained SOM is further processed by doing a k-means clustering of the node vectors, which then allows for the quantitative comparison of music trajectories between symphonies of the same composer, between symphonies of different composers of the same music period, and between composers from different music periods.

Each symphony is prepared by splitting the audio into 1-second segments. After which, jAudio 1.0.1 is used to extract the features from each segment, amounting to 78 features per segment, following the pre-processing steps from [1]. Once completed, the entire dataset is then normalized and clustered through Self-Organizing Maps.

The SOM is a 16 by 16-rectangular map, trained with a learning rate of 0.9 and a neighborhood distance of 16 during the initial learning phase. A global ordering phase of 10,000 cycles and a fine- tuning phase of another 10,000 cycles are used. The learning rate and neighborhood use a linear decay function decreasing to a value of 0.1 and 1 respectively by the completion of the global ordering phase. For the fine-tuning phase, the values of the learning rate and neighborhood are kept constant at 0.1 and 1, respectively.

Once a trained SOM is completed, the weights of each of the 256 nodes are clustered using k-means clustering. For the experiments conducted, we used k= 21, which resulted in clusters with at least 6 nodes in each of them. Fig. 1 is the clustered trained SOM, which we playfully refer to as a SOMphony.

Fig. 1. SOMphony Map using K = 21

Each cluster in the SOMphony is composed of nodes that are sensitive to specific types of music segments, with slight variations among the node weight vectors in each cluster. In other words, each 1-second music segment of a symphony would have a best-matching-unit (BMU) in one of the 21 clusters. Hence, if we play a given symphony that has been spliced into 1-second music segments, we can trace the sequence of BMU for the entire length of the musical piece and refer to this sequence as the "musical trajectory" of the symphony. Two symphonies that are similar would thus produce similar trajectories in the SOMphony.

In the next section, we do a subjective, qualitative comparison of the 45 different trajectories by visually inspecting them and comparing them pairwise to see whether certain symphonies "appear" to be similar to each other. For the visual inspection of the trajectories, the result of the k-means clustering is not yet used, as we pinpoint the exact BMU among the 256 nodes for each 1-second music segment. We then complement the qualitative assessment with a more objective quantitative comparison of the trajectories. It is this quantitative approach that directly involves the 21 clusters.

3 Comparison of Music Trajectories

3.1 Visual Rendering of the Music Trajectory on the Map

After obtaining the SOMphony Map, the symphony compositions are played in a way that for each 1-second segment of the composition, the BMU in the map is determined. The BMU is the one node among the 256 nodes in the map that is closest, based on the Euclidean distance, between the node weights and the features of the music segment. As explained earlier, this sequence of BMU nodes in the map is the music trajectory associated with the symphony. Figure 2 shows the individual trajectories for each of the 45 compositions, grouped by musical period.

In the visual inspection of the music trajectories, we denote using a color-encoding scheme the time sequence of music segments (blue are the earlier segments and the color moves towards red as the music progresses). This way, we can see where the music trajectory started and how the music traverses the SOMphony as the music unfolds. The notion of time is not used for the quantitative comparison of symphonies using cluster frequency counts. We simply use the normalized frequency counts once an entire symphony has been played out, and these cluster frequency counts are what we use to compare the similarity between symphonies. These are explained in greater detail in the next section.

For the first symphonies during the baroque period, the compositions were typically complex and being religious in nature, typically have repetitive sections and patterns, however they do not show any similarity in visualization and style between composers and their compositions as opposed to that of other periods. In contrast, the classical period hosts one of the most influential names in music, Mozart, where Figure 2 reveals that his Symphony 41, "Jupiter", has a diagonal movement which can also be seen from the compositions of almost all of the composers of the succeeding periods such as Mendelssohn, Schumann, Schubert, and Rachmaninov. Although these patterns could be seen from multiple composers after Mozart, the visualization does not allow any quantitative evidence that they are indeed related to each other.

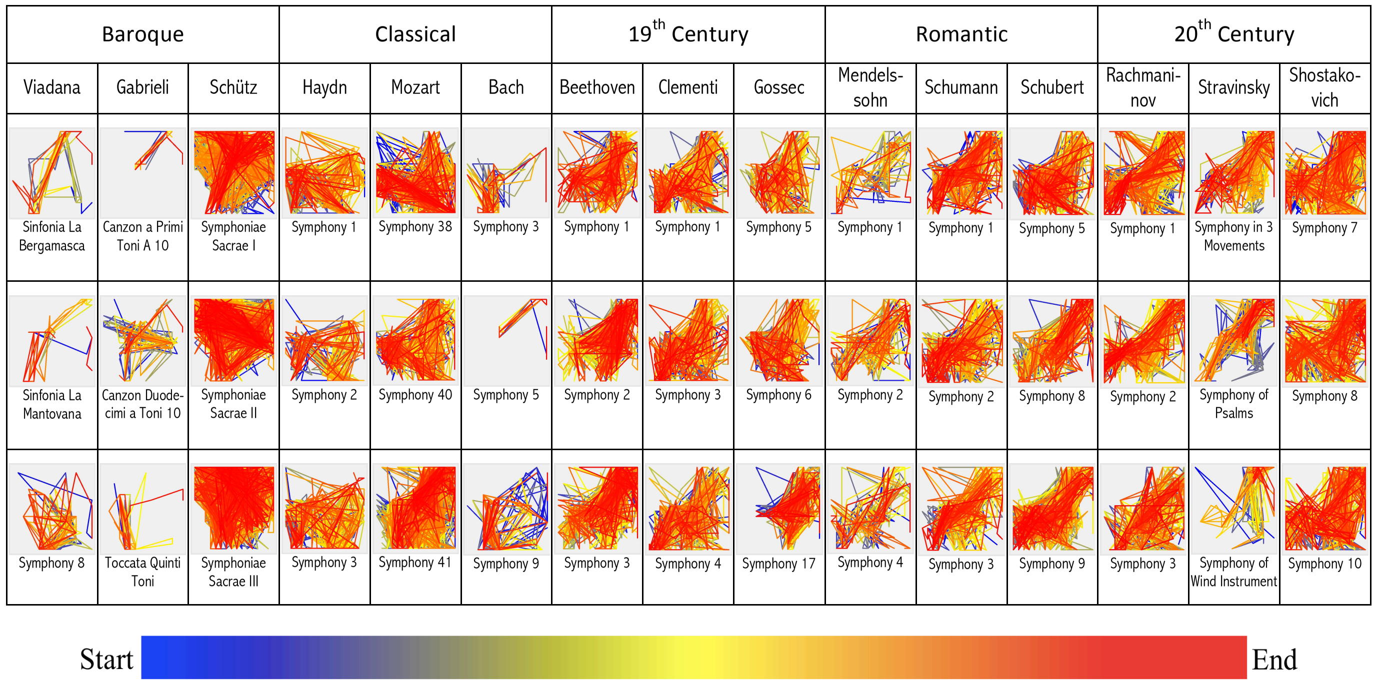

Fig. 2. SOMphony Trajectories and Color Spectrum to designate time in the SOMphony Map

3.2 Quantitative comparison among music trajectories

For each symphony, we keep track of the frequency count of each of the 21 clusters of nodes found using k-means clustering. Each time a 1-second music segment has a BMU within a certain cluster c(i), we increase the frequency count for cluster c(i). This way, if the symphony mainly uses music segments that have BMUs in among 3 clusters only, for example, then only these 3 clusters will have high frequency counts. We then normalize these frequency counts by dividing the counts of a given composition by its total number of 1-second music segment. A normalized count of s% for cluster c(i), for example, means that s% of the music segments had BMUs among the nodes contained in cluster c(i). Once these normalized frequencies have been summarized, it is now possible to use these percentages as basis for doing a pair-wise quantitative comparison among the 45 compositions to see which compositions can be considered to be similar with each other. We expect that some symphonies of the same composer would tend to be similar, if the composer has some coherent style. Also, there can be similarities among compositions of a given composer if another composer had heavily influenced him. Or a pair of compositions by different composers can turn out to be similar if these compositions have both been influenced heavily by the same (earlier) composer.

The pairwise comparisons between music trajectories are shown in Table 1. The comparisons are based on a simple Euclidean distance between the normalized frequency counts of composition 1 with those of composition 2. The smaller the entry, the more similar are the two compositions. In Table 2, we tag those distances of up to 0.2, in order to quickly see which are the pairs of symphonies with a relatively low distance between them.

We have opted to only include the quantitative comparisons for three musical periods, as these are where most of the pairs of similar symphonies can be seen. The compositions from the baroque period do not share similar trajectories with compositions of the same composer, nor with compositions of other composers of the same period. Neither do they resemble the compositions that appeared in the later centuries.

From Table 1, we discern two composers who seemed to have been very influential. During the Classical period, Mozart became one of the most famous composers of his time and is known to have been a huge influence in music. Table 1 indeed reveals similarities between Mozart's own compositions, implying some coherent style that Mozart may have developed. Furthermore, his compositions are also similar to those of a good number of composers during the 19th century following the classical period, namely Beethhoven, Clementi and Gossec, as well as the symphonic compositions of the Romantic and even the 20th century impressionist and post-impressionist era, including Mendelssohn, Schumann, Schubert, Rachmaninov and Shostakovich.

For the 19th Century musical period after Mozart, Beethoven became the most famous composer of his time and is also known to have a huge influence in music. Indeed, Table 1 reveals similarities between Beethoven's symphonies with those of the three Romantics (Mendelssohn, Schumann and Schubert), as well as Rachmaninov and even Stravinsky. And similar to Mozart, Beethoven also has a distinct style, and indeed, Table 1 also shows that Beethoven's compositions are quite similar to each other.

As to the Romantic period, it is interesting to note the similarity between compositions of the same composers, as well as the compositions among the three famous composers of this period. From Table 1, the pairwise comparisons among the compositions reveal that the music trajectories during this period were all of similar style. Worthwhile also to note is the fact that Gossec's symphonies of the 19th century resemble closely the works of the Romantics. And all the compositions from the Romantic period seemed to have carried over to the 20th century impressionist composers, especially Rachmaninov.

Table 1 also shows that some composers stick to their style of music, such as those of Beethoven, Clementi, Mendelssohn, and Schumann. However since the data is limited to the 3 compositions for each composer, not all possibilities are shown.

4 Conclusion

Self-Organizing Maps are shown to be indeed useful in visualizing symphonies as a musical trajectory across the nodes in a trained map. This allows for some insights about the relationships and influences between and among composers in terms of their composition styles, and how the symphonic compositions have evolved over the years from one major music period to the next. Even though the results presented a qualitative/subjective comparison of symphonies as well as an objective/quantitative mechanism for comparing symphonies, a larger dataset would be needed to confirm whether the approach is indeed valid. If proven to be so, it is clear that the approach described here may also be applied to other forms of music.

References

1. Azcarraga, A., Caronongan, A., Setiono, R., & Manalili, S. (2016). Validating the Stable Clustering of Songs in a Structured 3D SOM.
2. Corrêa, D. C., & Rodrigues, F. A. (2016). A survey on symbolic data-based music genre classification. *Expert Systems with Applications*, *60*, 190-210.
3. Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A k-means clustering algorithm. Journal of the Royal Statistical Society. Series C (Applied Statistics), 28(1), 100-108.
4. Kangas, J. A., Kohonen, T. K., & Laaksonen, J. T. (1990). Variants of self-organizing maps. Neural Networks, IEEE Transactions on, 1(1), 93-99.
5. Kohonen, T., & Somervuo, P. (1998). Self-organizing maps of symbol strings. Neurocomputing, 21(1), 19-30.
6. Scaringella, N., Zoia, G., & Mlynek, D. (2006). Automatic genre classification of music content: a survey. *IEEE Signal Processing Magazine*, *23*(2), 133-141.
7. Toussaint, G. T. (2003). Algorithmic, geometric, and combinatorial problems in computational music theory. *Proceedings of X Encuentros de Geometria Computacional*, 101-107.
8. Ultsch, A. (1993). Self-organizing neural networks for visualisation and classification. In *Information and classification* (pp. 307-313). Springer Berlin Heidelberg.

Table 1. Pairwise Euclidean Distance Comparison of Symphony Clusters

Distance		Classical									19th Century									Romantic									20th Century								
		H1	H2	H3	M1	M2	M3	B1	B2	B3	B1	B2	B3	C1	C2	C2	G1	G2	G3	M1	M1	M3	SM1	SM2	SM3	SB1	SB2	SB3	R1	R2	R3	ST1	ST2	ST3	SH1	SH2	SH3
Classical	Haydn 1		14	7	25	25	30	30	76	31	26	27	31	25	27	30	35	29	27	26	28	28	24	22	22	29	33	31	32	34	32	46	48	65	32	34	33
	Haydn 2			15	29	29	32	37	76	36	29	31	34	30	34	38	36	34	31	27	32	32	30	30	29	34	35	36	33	39	38	47	50	65	34	32	33
	Haydn 3				25	24	28	28	75	30	28	30	31	23	24	28	36	29	29	25	27	27	27	22	24	28	32	30	31	33	29	45	47	64	30	32	32
	Mozart 1					15	27	30	79	41	32	36	35	18	31	30	41	23	25	31	27	25	32	18	28	17	33	24	31	27	23	48	51	66	31	34	34
	Mozart 2						16	32	70	42	22	28	23	14	27	29	33	16	15	23	19	18	23	12	20	10	23	11	20	15	21	36	39	55	21	26	25
	Mozart 3							38	58	43	21	27	19	20	29	31	24	20	16	15	12	11	26	24	27	20	14	15	15	19	22	26	28	45	10	16	15
	Bach 1								84	25	44	47	45	30	32	33	53	34	39	42	38	35	40	29	37	31	43	34	42	36	34	55	56	72	40	44	44
	Bach 2									82	58	57	52	74	77	78	57	74	67	57	63	63	67	74	69	75	50	65	53	63	74	38	41	39	52	50	47
	Bach 3										45	47	48	42	41	43	53	43	44	45	44	41	46	42	45	44	47	46	46	48	46	56	57	70	46	48	46
19th Century	Beethoven 1											10	8	29	35	38	25	29	21	19	25	26	16	25	20	29	19	23	16	24	36	25	29	46	21	23	20
	Beethoven 2												12	34	39	42	27	35	27	22	30	31	16	28	18	35	23	29	20	29	41	28	33	49	26	27	24
	Beethoven 3													29	36	38	25	30	21	18	24	25	18	27	21	30	14	22	11	22	36	19	24	41	18	20	16
	Clementi 1														16	16	35	18	19	23	17	16	27	16	25	13	25	17	25	22	13	41	42	60	23	29	28
	Clementi 2															9	41	30	30	28	26	25	33	26	31	28	32	29	33	33	22	47	44	63	30	36	35
	Clementi 3																42	29	30	31	27	25	36	28	35	27	33	30	35	34	18	48	46	66	32	39	37
	Gossec 1																	30	24	21	21	23	29	36	32	36	24	33	28	35	35	33	36	55	26	28	26
	Gossec 2																		11	27	16	16	26	18	27	12	28	18	28	22	20	41	43	61	27	33	32
	Gossec 3																			21	15	15	21	20	24	17	21	17	20	21	24	33	37	55	22	27	25
Romantic	Mendelssohn 1																				15	17	23	27	25	28	13	24	16	27	28	28	29	48	15	15	14
	Mendelssohn 2																					7	25	23	26	19	18	19	21	23	17	34	35	55	17	22	21
	Mendelssohn 3																						27	22	28	18	17	18	21	22	15	33	35	54	16	23	21
	Schumann 1																							19	10	27	26	23	22	24	35	35	39	57	28	31	29
	Schumann 2																								14	13	29	16	26	17	24	42	45	63	27	32	31
	Schumann 3																									25	28	23	24	23	33	39	42	60	28	31	30
	Schubert 1																										28	13	26	16	17	42	44	62	25	31	31
	Schubert 2																											20	9	22	28	19	22	41	11	14	9
	Schubert 3																												18	6	22	31	34	51	17	24	23