Scene Detection in Skiing Videos

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Bachelor's thesis

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Abstract

In alpine skiing, video motion analysis provides high level physiological and performance data. However, interpreting this data correctly requires a good eye, knowledge and experience. An artificial assistant could support inexperienced skiers as well as trainers, athletes and sports journalists to discern areas of possible improvement. For the artificial assistant to achieve the best results, a high quality input such as videos from broadcasted ski races is required.

These events are usually transmitted as a series of runs, each caught from different camera perspectives per competing athlete. The video segment from one athlete and one camera view point has position and feature continuity between its frames. Without this continuity, performance analysis algorithms based on concluded sequences such as joint movement or trajectory tracking would not work. This raises the need for a scene detection tool.

In the following bachelor's thesis, an application capable of detecting scene cuts in broadcasted ski races is developed, optimised and its results evaluated.

First, a representative broadcast is labeled manually to define the ground truth for the three occurring transitions: Cut, wipe and dissolve. To ensure the detection of a scene change, each transition needs to be covered by a separate algorithm. The cut algorithm makes use of the frame differences between two camera angles by calculating the overall pixel change in the HSV colour space. By developing a valid measure of quality an optimal threshold value for the calculated pixel change is determined.

Due to the complexity and differences in occurrence, wipes and dissolves will not be taken into consideration in this thesis.

Although the developed algorithm takes nine times longer than Blackmagic Design's Da Vinci Resolve auto scene detector, it is still competitive in terms of quality. On top, the application can be extended and used fully automatically where the competition requires manual input and an additional parsing script for further processing.

The objective is achieved. Both the developed and the professional application detect scenes to an acceptable degree. With the scripted parsing tools and additional manual input during processing, Da Vinci Resolve can be used for the articial assistant's scene detection while the developed application is extended by wipe and dissolve detectors.

Contents

1 Introduction

1.1 Background

In competitive sports, video motion analysis is a very common method used by coaches to give detailed feedback to an athlete or a team. After recording the sportsperson in action on video, software is used to show recent performance and directly address the areas of possible improvement. This especially applies to alpine skiing, a highly techno motor kind of sport where a hundredth of a second can decide victory or defeat. Until now, after capturing the motion sequence to analyse, a trainer would first watch the video and then work out the corrective measures with the most impact. The athlete would then join in and receive feedback based on the representative performance on tape. Figure 1.1 demonstrates how exercises and their adaptation in muscle memory lead to the beginning of a new training cycle.

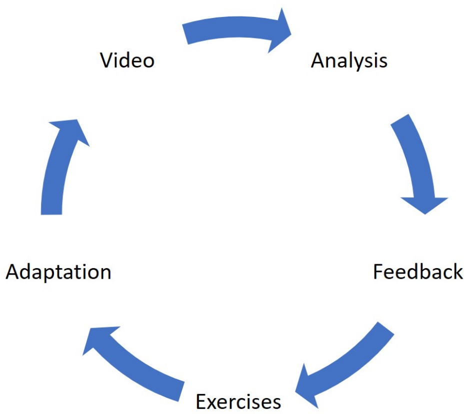


Figure 1.1: Training process with video motion analysis.

Unfortunately, there is no ideal position or technique in skiing, the result of each run is only judged by the time it took the athlete from start to finish. Over the past years of training theory, a guiding model was developed to refer to regarding the skier's position, timing of change or choice of line. Yet practice shows, that accurately applying the model to a training or racing situation requires a good eye to spot the slightest differences, profound knowledge in skiing theory and years of experience.

1.2 Motivation

An artificial assistant could be the solution to support inexperienced skiers as well as trainers, athletes or sports journalists improving their judgment. The guiding model can serve as the reference for a computer to learn the characteristics that define a good turn. By comparing the visual data of a video with the given model, a program could then figure out the major differences and therefore not only classify a good or a bad turn, but discern possible areas of improvement for proper feedback. Matching the given feedback to suitable exercises could enable active training suggestions. The flow chart in figure 1.2 points out one possible process for such an artificial assistant.

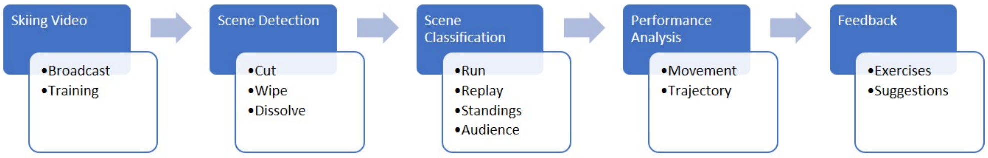


Figure 1.2: With visual input the artificial assistant could give training suggestions.

The first step to this artificial assistant is the ability to analyse and assess an athlete's skiing performance, shown in figure 1.3. The techniques and kinematics are especially important as they can be influenced and adjusted directly in action. In techniques, the most noteworthy element is the skier's position and how it changes over the course of the turn. Important joints like ankles, knees, hip joints or shoulders can be detected and their movement traced using pose estimation. In kinematics, besides skiing physics, the choice of line is worth mentioning. The sportsperson and gates can be identified via object detection and their relative shift with the resulting trajectory tracked by the optical flow. However, all of these approaches assume that the input is a series of time-consecutive frames taken from the same camera angle.

For the assistant to achieve the best results, a high quality input such as videos from broadcasted ski races is required. These events are usually transmitted as a series of runs, each caught from different camera perspectives per competing athlete. The video segment from one athlete and one camera view point has position and feature continuity between its frames. Without this continuity, the previously mentioned performance analysis algorithms would not work. The integration of start list, standings and repetitions further complicates the assessment. This raises the need for a scene detection tool.

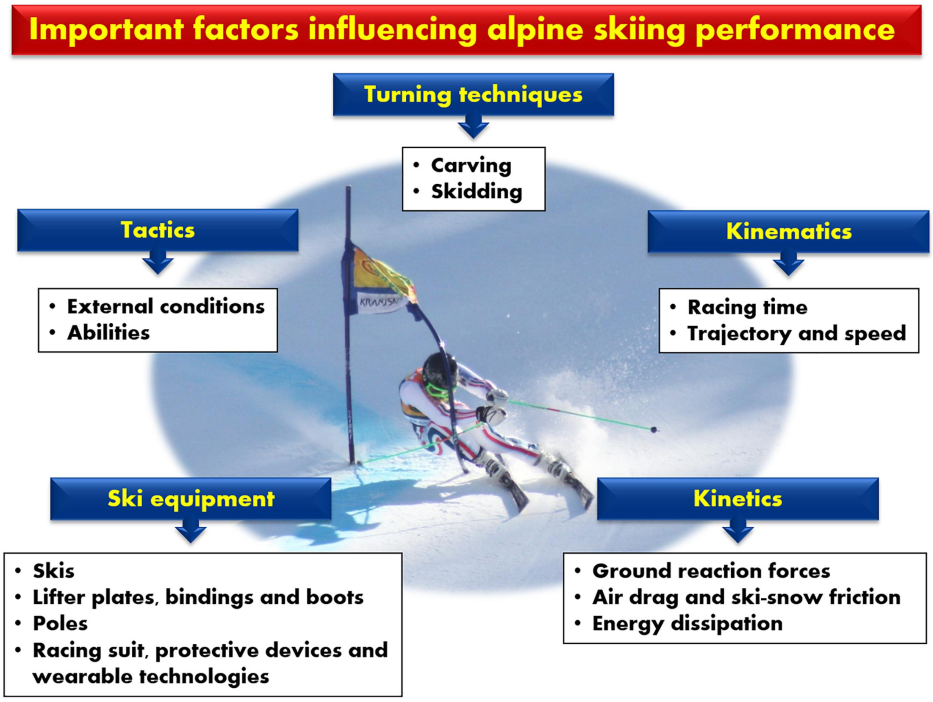


Figure 1.3: Techniques and kinematics can be influenced and adjusted directly in action. [5]

1.3 State of the Art

Scene Detection is a well-known problem not only in video analysis but more so in the post-production of film industry. Video editors spend hours manually splitting and putting together the right shots. Naturally, companies like FFmpeg, FCP, or Adobe Premiere implemented scene detection tools in their software.

Many of these video editing applications do not offer a free version, and those who do, make the scene-detection feature inaccessible or drastically reduce its functionality. The remaining tools, when documented, often make use of the PySceneDetect library.

The generally most recommended software is Blackmagic Design's Da Vinci Resolve (lite). But even there the documentation quotes: "Dissolves and other transitions are not automatically detected[...]." It also warns that sudden jumps in the motion of the frame or abrupt change in color or lighting all can fool the scene detection algorithm.[7] These are sub-optimal conditions for inevitably high-motion racing recordings. Nevertheless, as highly regarded freeware Da Vinci Resolve will be used as benchmark in accuracy for the detected scenes.

1.4 Approach

First, the data material provided by the DSV[1] is sifted and a representative video broadcast[2] is selected. This broadcast is then manually labeled for the three occurring transitions: cut, wipe and dissolve. Furthermore, each scene is classified by the camera view point and extraordinary events like standings or mistakes. The so created ground table is attached in the appendix on page 27.

To ensure the detection of a scene change, each transition needs to be covered by a separate algorithm. The cut algorithm makes use of the frame differences between two camera angles by calculating the overall pixel change in the HSV colour space.[3] Due to the complexity and differences in occurrence, wipes and dissolves will not be taken into consideration in this thesis.

1.5 Objective

With the greater goal of a fully implemented artificial coach in mind, the objective of this bachelor's thesis is to develop an application capable of detecting scene cuts in broadcasted ski races. Once it can do so, methods of optimisation are implemented and discussed. Finally, its results are evaluated by comparing the developed tool with existing scene cut detectors.

[1] Deutscher Skiverband

[2] The same broadcasted race is also uploaded in youtube with the following link: `https://www.youtube.com/watch?v=w9C7-V2c0F4`

[3] Hue, Saturation, Value. More information in section 2.2 on page 12.

2 Theory

2.1 Scene Transitions

2.1.1 Cut

The cut is the most common transition format between two scenes. It is also the most basic in that the broadcast undergoes no special processes; the two shots are simply played one after the other. While watching the broadcast, this is where one image on screen is instantly replaced with another, often in the form of a camera angle change. Thus, as shown in figure 2.1, a cut only appears between two frames.

(a) Frame 28442 **(b)** Frame 28443 **(c)** Frame 28444

Figure 2.1: Cut between (b) and (c): The shots are taken simultaneously as shown by the time overlay.

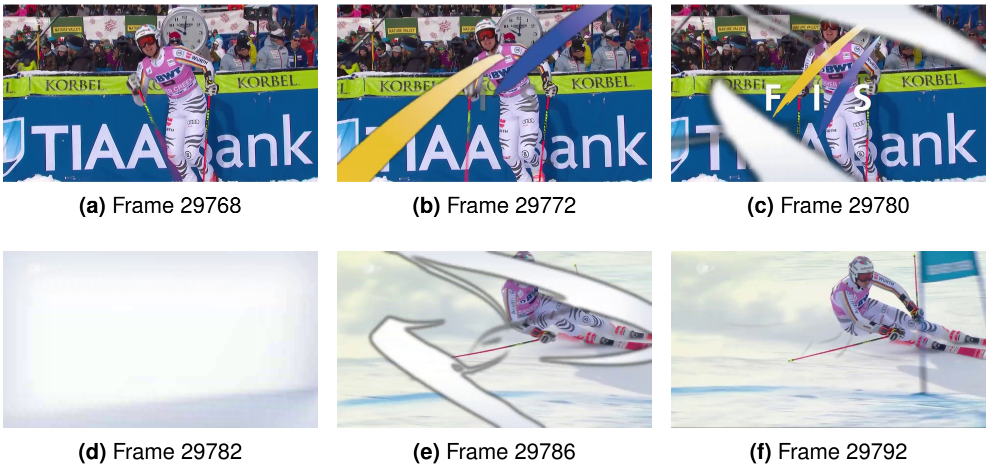
2.1.2 Wipe

Wipes are types of scene transition where one shot replaces another by travelling from one side of the frame to another or with a special shape. In case of the broadcast, the frame is sliced by the FIS logo[1] before making space for the next scene. Wipes take a couple of frames to fully replace the old shot with the new one. Figure 2.2 shows the contrast to a cut where there is no such transition.

2.1.3 Dissolve

A dissolve involves gradually decreasing the visibility of one shot while increasing the visibility of another. For the duration of the effect the dissolve overlaps the two

[1] Fédération Internationale de Ski

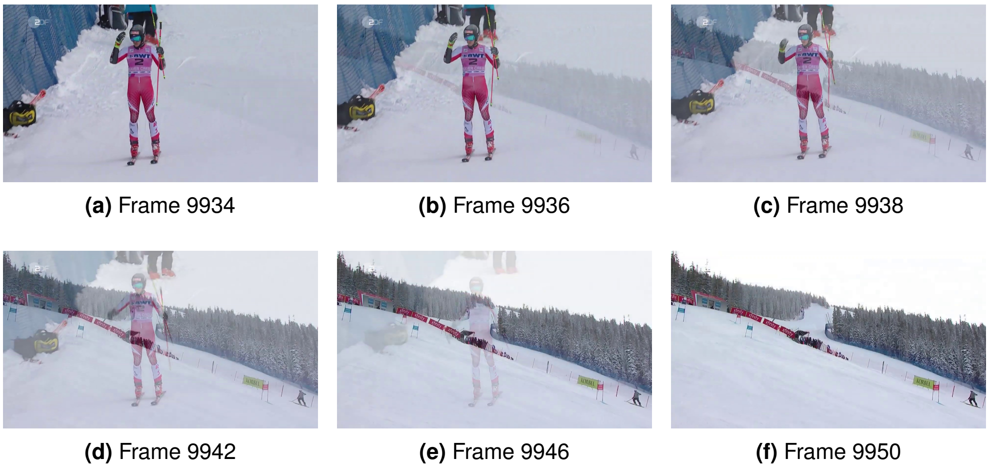


(a) Frame 29768 **(b)** Frame 29772 **(c)** Frame 29780

(d) Frame 29782 **(e)** Frame 29786 **(f)** Frame 29792

Figure 2.2: Wipe: The FIS logo slowly slices away the old shot.

shots showing both at the same time as illustrated in figure 2.3. Just like the wipe the dissolve takes a few frames to transform into the new scene.



(a) Frame 9934 **(b)** Frame 9936 **(c)** Frame 9938

(d) Frame 9942 **(e)** Frame 9946 **(f)** Frame 9950

Figure 2.3: Dissolve: The new shot seems to appear behind the fading old one.

2.2 HSV Colour Space

The HSV colour space is one out of many different abstract mathematical models describing the way colours can be represented as tuples of numbers. The three name giving letters represent hue, saturation and value, where value can be interpreted as brightness. These attributes span an inverted cone as shown in figure 2.4. In contrast to many other colour spaces, this one feels more natural for the human observer as the model defines different colours with attributes commonly used in the description of colours. For this reason, many software applications (open-source examples are Blender, GIMP, Inkscape, and Krita) include color pickers which try to cater to our perception of colors in the terms mentioned above. [3] [11]

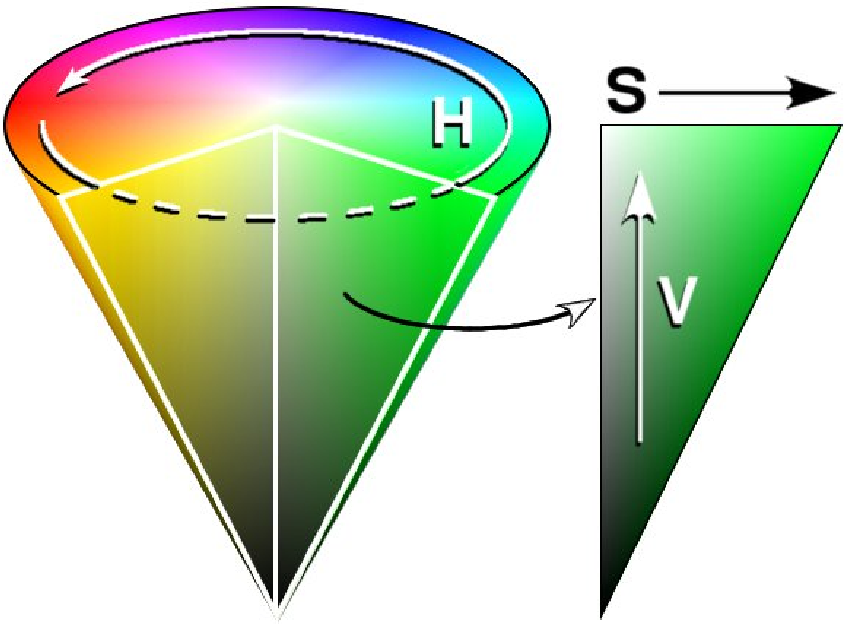


Figure 2.4: Hue, saturation and value span the conic HSV colour space. [8]

3 Implementation

3.1 Metric

To find an appropriate measure for the application's quality, one must first think about all possible outcomes when detecting scenes in a given video. In addition, their relative frequency must be taken into account to avoid distorting the final result as the data set might be imbalanced. [9]

As a representative video the world cup's first run of giant slalom in Beaver Creek (USA), broadcasted on 2nd December 2018, is selected. It is around one hour long with 25 frames per second. The broadcast begins by showing the start list, before jumping into the race with the first athlete. From then on, the race is only interrupted by track preparation pauses in which the intermediate standings and repetitions are displayed.

The video is analysed frame by frame to define the ground truth. When a transition occurs, either between two frames or over the length of multiple frames, the frame's index number together with the corresponding transition type is noted in a csv file.[1] Furthermore, each scene is classified by the bib number and camera view point to make the file more readable to the human eye and simplify future development in section classifications. Lastly, uncommon events such as repetitions, standings or mistakes are added in an extra column. As shown in the appendix on page 27, a total of 86658 frames with 401 resulting scenes are entered in the ground truth table, 307 of them are direct cuts, 62 cross dissolves and 32 FIS Wipes.

When done calculating through the broadcast, the application will assign Boolean values to each frame: "True" labeled frames indicate a detected transition while "False" means no transition detected. The ground truth meanwhile has all transitions listed, ergo a listed frame is "True" while an ignored one is "False". As shown in the following table in figure 3.1, each frame can therefore be in one of four categories: Correct detection (C), false detection (F), missed detection (M) or no detection (N).[10]

One seemingly obvious metric to assess the algorithm's quality would be dividing the sum of all frames with matching Boolean values by the total sum of all analysed frames. With only about 0.5% of all frames being cuts, this accuracy (A) called metric would heavily rely on the other 99.5%. As shown in equation 3.1, an algorithm

[1] Comma-separated Values

		Ground Truth Transition	
		Positive	Negative
Transition in Detection	Positive	C	F
	Negative	M	N

Figure 3.1: The four categories of a frame classification: correct, false, missed and none.

without a single correct detection would still achieve an astonishing 99.5% accuracy, so optimising the application with this metric won't deliver promising results.

$$A = \frac{C+N}{C+M+F+N}(= \frac{0+0.995}{0+0.005+0+0.995} = 0.995 \rightarrow 99.5\%) \quad (3.1)$$

To focus the quality measurement on the detected rather than all other frames it is recommended to ignore the category of true negatives (N). In case the false positives (F) are ignored, too, that leaves a measure called recall (R) as shown in equation 3.2. Using recall as the metric of choice provides the probability that an existing cut will be detected. That makes sense, as long as the algorithm is not too eager to classify frames as transitions. Otherwise a similar problem to the already identified one will render the measure useless: As false positives (F) don't influence the recall in a negative way, a pure transition classification for each frame leaves the algorithm with a clean score of 100%.

$$R = \frac{C}{C+M}(= \frac{1}{1+0} = 1 \rightarrow 100\%) \quad (3.2)$$

Precision is a metric that gives the probability of an assumed cut being in fact a cut. Because it takes all frames listed in the ground truth into account there is no loophole to exploit the metric in case of pure classification. Still, equation 3.3 shows that having one single correct detection with all other frames classified as non transitions is sufficient for the optimal measure result.

$$P = \frac{C}{C+F}(= \frac{1}{1+0} = 1 \rightarrow 100\%) \quad (3.3)$$

Depending on the algorithms tendency to either detect too few real or too many non existent transitions, recall and precision can help a great deal to optimise those specific errors. But to get a valuable overall assessment a hybrid between both metrics is needed. [1] One such suggestion is portrayed in equation 3.4. While only correctly classified real transitions increase the developed quality measure (Q), both missed real transitions and wrongly detected frames decrease the score. This metric sets very high general standards, so a few deviations are made for each detector. [9]

$$Q = \frac{C}{C + M + F} \tag{3.4}$$

The cut detection algorithm makes use of the frame differences between two camera perspectives by calculating the overall pixel change in the HSV colour space. Problematically, wipes and dissolves also feature many pixel changes in their transition progress. As a consequence the cut detection algorithm might detect cuts for each frame within these transitions. While a true cut happens between two frames and can thus be detected only once, wrong cuts detected within transitions would drastically falsify any metric as for each transition many frames could be detected.

To recieve a clean quality measure for the cut detection algorithm alone without disproportionate change by other transition's influence, the idea is to completely neglect frames within the other transitions types. After running the algorithm and generating the list of detected cut frames, every frame occurring in a different transition is then deleted from this list and the remainders are used to calculate the true metric.

Following the four categories in figure 3.1, the cut detector's quality ($Q_{\text{cut detector}}$) can be calculated with the following adaptations of parameters from equation 3.4:

- C - correctly detected transition frames, that are neither a wipe nor a dissolve
- F - falsely detected transition frames, that are neither a wipe nor a dissolve
- M - missed transition frames, that are neither a wipe nor a dissolve

3.2 Cut Detection

Using the integrated development environment PyCharm and the programming language Python, the biggest task is the creation of a cut detection algorithm.

3.2.1 HSV Content Value

The analysed part of the selected broadcast has a total of 86658 frames. With a resolution of 720p, each of those frames has 1280x720 pixels. Every pixel again can be represented in the HSV colour space with the three attributes hue, saturation and value as shown in figure 2.4. For every pixel these attributes of two consecutive frames are compared to gain information about the gradient of change. For each attribute, the sum of all pixel changes divided by the number of pixels gives the mean average of the frame change in respect to this attribute. Taking the mean average of those three attributes again results in a fourth attribute, here called content value, representing the overall frame change. The larger the content value is for a given frame, the more it has changed from the previous one.

In figure 3.2 it can easily be seen, that the abrupt scene changes necessary to follow the athletes during the race correlate with the intensive content value spikes. This supports the theory of the content value being a good indicator for a scene cut. Furthermore, every larger gap between these spikes can be explained by preparation breaks[2] as pointed out by the red arrows. With slow motion repetitions, standings and sequences of the audience or the winner's box no quick scene cuts are needed to stay with the action. Instead the recipient is given more time to read the tables with only a minimum amount of change in the background.

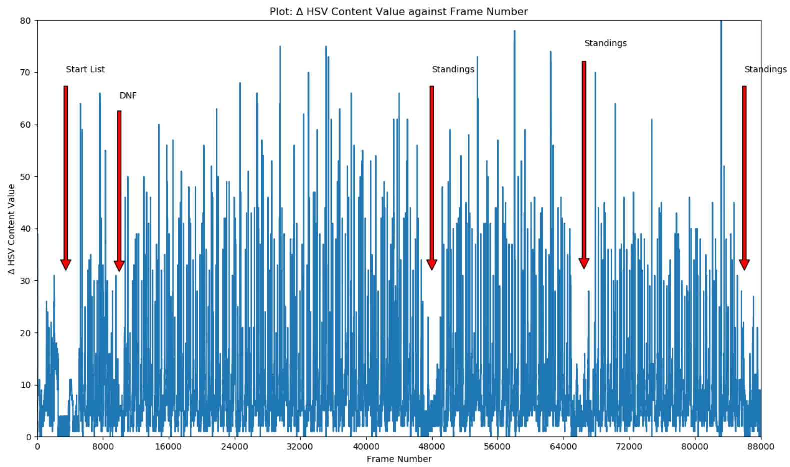


Figure 3.2: Frame wise comparison of content values enables the algorithm to detect a cut.

PySceneDetect is the main library used for the implementation of this cut detection algorithm. With some deviations it takes roughly ninety minutes to fully process the broadcast of one hour length. For each frame the named four attributes are saved in a csv file, drastically speeding up processing time for the threshold calculation in the course. That also leaves the option to later on weight individual attributes differently, e.g. focusing more on hue and less on saturation.

3.2.2 Threshold

Having generated all respective content values, the next step is to determine the ideal threshold value for the scene detector. Figure 3.3 gives an overview of the content value distribution. It becomes apparent that the threshold is very likely to be above twenty.

[2] DNF is the skiing term for 'Did not finish' and means an athlete stopped racing the course. It often goes with a short preparation break to wait for the next athlete to get in the starting position.

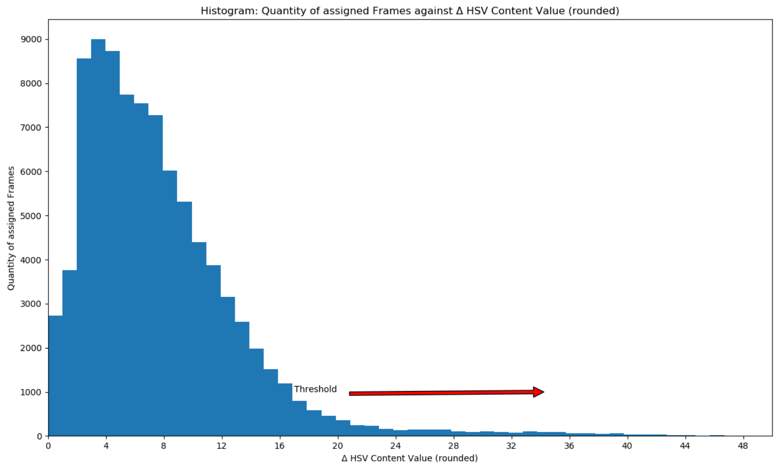


Figure 3.3: The content value distribution gives information on the threshold.

To find the best threshold for the given broadcast the csv file containing the processed content values is used. For each threshold value, beginning with zero and ending with sixty, the amount of correct detections (C), false detections (F) and missed detections (M) are evaluated and used to calculate recall, precision and the overall quality measure. The result is attached on page 39 of the appendix and visualised in figure 3.4.

As predicted in equation 3.2 a low threshold value easily scores a high recall value as only few true cuts will be missed. Vice versa, only a vast minority of frame changes with high scoring content values is not a true cut, so explainable by equation 3.3 a high threshold value leads to few false detections resulting in a high precision. The best measure of quality (Q) is scored by the threshold value forty, with 42.3%. It comes with a 48.4% recall value and a 77.1% precision.

With the threshold value established and its metrics known, the developed scene cut detector is now ready to be compared to Da Vinci Resolve's auto scene detect module.

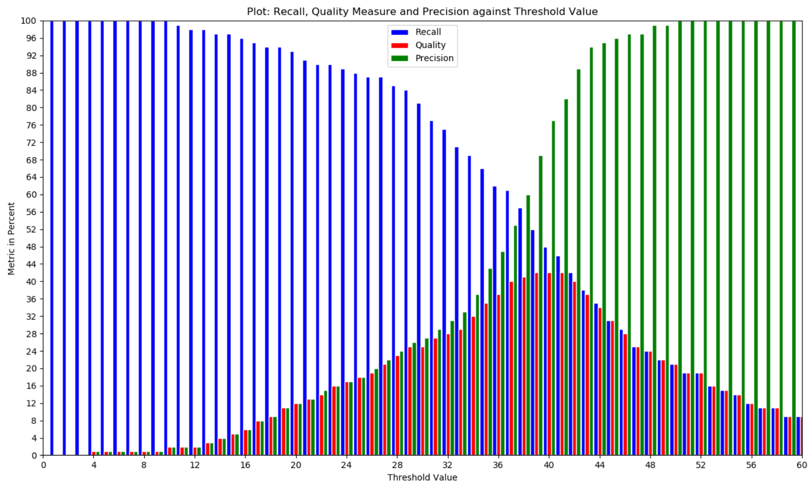


Figure 3.4: Increasing the threshold lowers the recall but increases the precision. Threshold values close to their graphic intersection score highest in the measure of quality.

4 Results

The developed cut algorithm can only be properly evaluated when compared to an existing tool. One such tool is Blackmagic Design's Da Vinci Resolve (lite). But even there the documentation quotes: "NOTE: Dissolves and other transitions are not automatically detected[...]." It also warns that sudden jumps in the motion of the frame or abrupt change in color or lighting all can fool the scene detection algorithm. These are sub-optimal conditions for inevitably high-motion racing recordings. Nevertheless, as highly regarded freeware Da Vinci Resolve will be used as benchmark in accuracy for the detected scenes.

After importing the same broadcast as used in the development of the application into the working panel and selecting the 'auto scene detect', Da Vinci Resolve only takes a bit less than ten minutes to completely analyse the video where the hand coded cut detection needed nine times as much. It also calculates and assigns a specific likelihood value to each frame and shows the self chosen threshold as a horizontal magenta confidence bar through the green likelihood spikes, as shown in figure 4.1. On the right hand side, a table with all suggested scenes, their frames and their time codes is presented. Triggering a left click-event on any scene is followed by an update of the three presented frames on top of the panel, easily enabling to verify the detected scene cut.

Unfortunately, there is no easy option to directly save the table but to export it in an edl file[1] which only carries the time codes. That is an annoying inconvenience while testing, but could be a real hindrance in the workflow later on. With a converted file and parsed time codes generated by a handwritten script, Da Vinci Resolve's suggestion can finally be exposed to the quality measures.

The suggestion is first filtered in two sets: One data set keeps the detected FIS wipes and cross dissolves while the other one, like the developed algorithm, is only measured by true cuts. The metric of both sets can be looked up in the appendix on page 40.

In direct comparison to the developed cut detector's best scoring threshold value Da Vinci Resolve's auto scene detection already scores acceptable without evening the ground by ignoring wipes and dissolves. Especially the precision value of 84,96% whilst still scoring 36,31% in recall leads to a rather high measure of quality with 34,11%. That is among the top ten values and thus the high end of the application's threshold suggestions.

[1] Edit Decision List

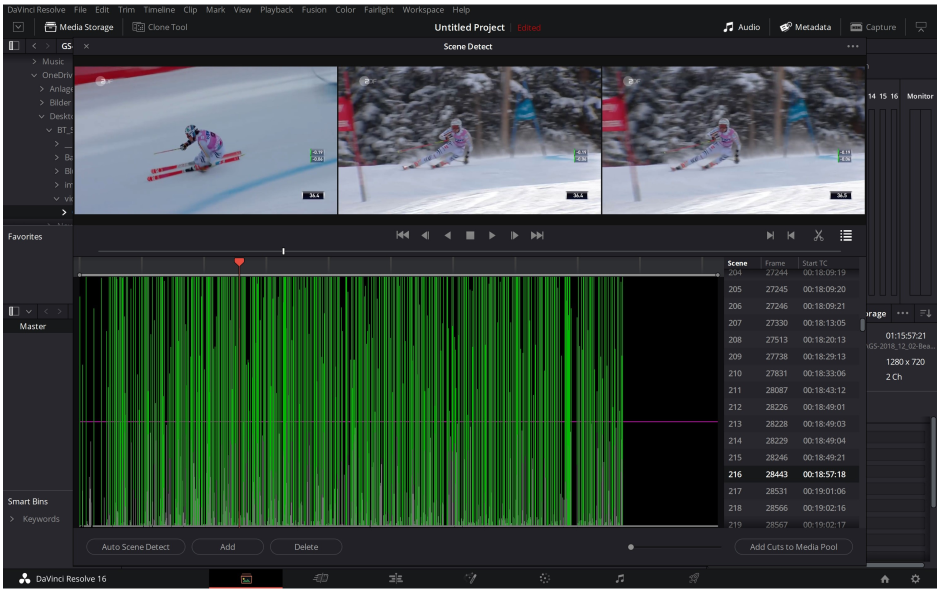


Figure 4.1: Da Vinci's auto scene detect module with its features.

With the adjusted data set for an equitable metric use Blackmagic Design's freeware solution ends up on top as shown in the following figure 4.2. Except for the precision value, Da Vinci is superior in every other metric.[2]

[2]The F1 score is comparable to the Q score, but with double the weight on correct detections.

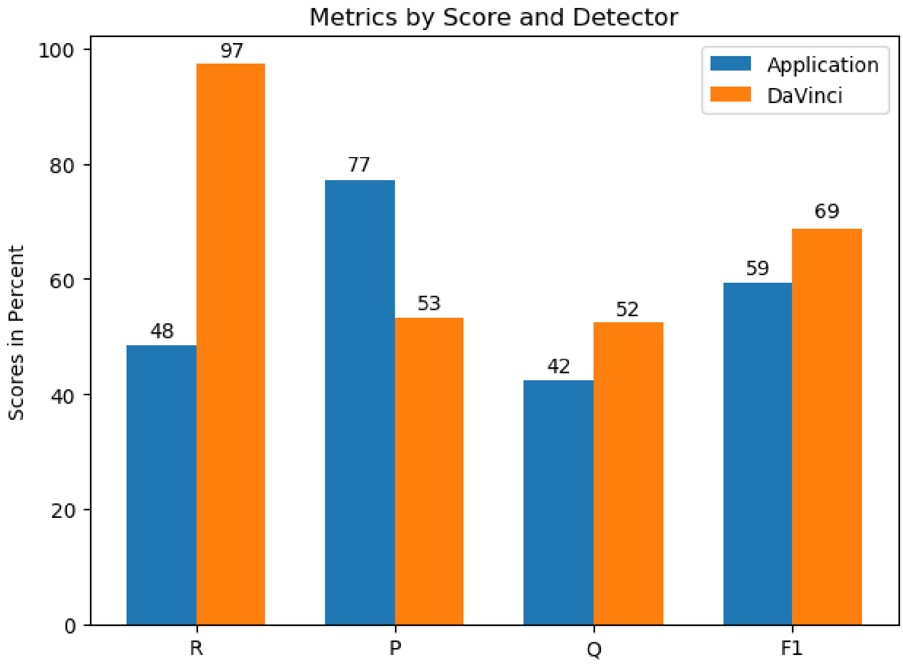


Figure 4.2: Comparison of the achieved metrics by Da Vinci and the developed application.

5 Conclusion

With the greater goal of a fully implemented artificial coach in mind, an application has been developed, that is capable of detecting scene cuts in broadcasted ski races. The application has been measured by a thought through metric respecting all eventualities and optimized by shifting the threshold parameter over the thoroughly calculated and frame wise assigned HSV content values. Making use of OpenCV, the python API and the PySceneDetect library, it has been possible to create a function that scores comparable to one of the market leading developers in video editing software.

Both the developed and the professional application detect scenes to a more than acceptable degree. The developed application's clear advantages are mainly the possibility to fully automatise all processes while also being extendable for e.g. a wipe or a dissolve detector. Also its decision making behind a cut classification is completely comprehensible.

Da Vinci Resolve surpasses the developed application's processing time by the factor nine though and still scores slightly better in the quality measure. Those facts for now totally make up for the disadvantages: The need of an additionally scripted parsing tool and permanent manual input for each new video during processing. Da Vinci Resolve can be used for the articial assistant's scene detection while the developed application is extended and further optimised.

Appendix

Ground Truth Table

Scene	Start Frame	End Frame	diff	Bib Number	Section	Note
1	1	64	64		Intro	
2	65	529	465		Gate 50 to 55	
3	530	545	16		Dissolve	
4	546	1.164	619		Forest	
5	1.165	1.169	5		Dissolve	
6	1.170	2.016	847		Start Preparation	
7	2.017	2.032	16		Dissolve	
8	2.033	2.559	527		Stands	
9	2.560	2.571	12		Dissolve	
10	2.572	3.866	1.295			Start List
11	3.867	3.885	19		Dissolve	
12	3.886	4.367	482		Gate 50 to 55	
13	4.368	4.378	11		Dissolve	
14	4.379	4.807	429		Gate 07 to 19	
15	4.808	4.820	13		Dissolve	
16	4.821	5.092	272		Start House	
17	5.093	5.104	12		Dissolve	
18	5.105	5.281	177		Start Preparation	
19	5.282	5.493	212		Start House	
20	5.494	5.841	348	1	Gate 01 to 07	
21	5.842	6.174	333	1	Gate 07 to 19	
22	6.175	6.343	169	1	Gate 19 to 25	
23	6.344	6.533	190	1	Gate 25 to 31	
24	6.534	6.660	127	1	Gate 31 to 35	
25	6.661	6.948	288	1	Gate 35 to 43	
26	6.949	7.177	229	1	Gate 43 to 50	
27	7.178	7.328	151	1	Gate 50 to 55	
28	7.329	7.546	218	1	Gate 55 to 60	
29	7.547	7.640	94		Finish	
30	7.641	7.690	50		Stands	
31	7.691	7.790	100		Finish	

32	7.791	7.814	24		FIS Wipe	
33	7.815	7.997	183			Repetition
34	7.998	8.018	21		FIS Wipe	
35	8.019	8.079	61		Finish	
36	8.080	8.091	12		Dissolve	
37	8.092	8.317	226		Start House	
38	8.318	8.555	238	2	Gate 01 to 07	Mistake
39	8.556	9.183	628	2	Gate 07 to 19	Out
40	9.184	9.207	24		FIS Wipe	
41	9.208	9.592	385		Gate 01 to 07	Repetition
42	9.593	9.612	20		FIS Wipe	
43	9.613	9.933	321		Gate 07 to 19	Out
44	9.934	9.949	16		Dissolve	
45	9.950	10.328	379		Gate 01 to 07	
46	10.329	10.341	13		Dissolve	
47	10.342	10.619	278		Winner’s Box	
48	10.620	10.630	11		Dissolve	
49	10.631	10.719	89		Start Preparation	
50	10.720	11.046	327		Start House	
51	11.047	11.305	259	3	Gate 01 to 07	
52	11.306	11.617	312	3	Gate 07 to 19	
53	11.618	11.794	177	3	Gate 19 to 25	
54	11.795	11.977	183	3	Gate 25 to 31	
55	11.978	12.114	137	3	Gate 31 to 35	
56	12.115	12.362	248	3	Gate 35 to 43	
57	12.363	12.645	283	3	Gate 43 to 50	
58	12.646	12.740	95	3	Gate 50 to 55	
59	12.741	13.011	271	3	Gate 55 to 60	
60	13.012	13.320	309		Finish	
61	13.321	13.344	24		FIS Wipe	
62	13.345	13.558	214			Repetition
63	13.559	13.578	20		FIS Wipe	
64	13.579	13.624	46		Finish	
65	13.625	13.637	13		Dissolve	
66	13.638	13.810	173		Start House	
67	13.811	14.053	243	4	Gate 01 to 07	
68	14.054	14.371	318	4	Gate 07 to 19	
69	14.372	14.541	170	4	Gate 19 to 25	
70	14.542	14.733	192	4	Gate 25 to 31	
71	14.734	14.824	91	4	Gate 31 to 35	
72	14.825	15.120	296	4	Gate 35 to 43	
73	15.121	15.385	265	4	Gate 43 to 50	

74	15.386	15.531	146	4	Gate 50 to 55	
75	15.532	15.789	258	4	Gate 55 to 60	
76	15.790	16.036	247		Finish	
77	16.037	16.061	25		FIS Wipe	
78	16.062	16.260	199			Repetition
79	16.261	16.280	20		FIS Wipe	
80	16.281	16.534	254		Start House	
81	16.535	16.748	214	5	Gate 01 to 07	
82	16.749	17.093	345	5	Gate 07 to 19	
83	17.094	17.261	168	5	Gate 19 to 25	
84	17.262	17.438	177	5	Gate 25 to 31	
85	17.439	17.547	109	5	Gate 31 to 35	
86	17.548	17.828	281	5	Gate 35 to 43	
87	17.829	18.084	256	5	Gate 43 to 50	
88	18.085	18.238	154	5	Gate 50 to 55	
89	18.239	18.465	227	5	Gate 55 to 60	
90	18.466	18.656	191		Finish	
91	18.657	18.680	24		FIS Wipe	
92	18.681	18.965	285			Repetition
93	18.966	18.985	20		FIS Wipe	
94	18.986	19.029	44		Winner's Box	Way
95	19.030	19.042	13		Dissolve	
96	19.043	19.267	225		Start House	
97	19.268	19.469	202	6	Gate 01 to 07	
98	19.470	19.826	357	6	Gate 07 to 19	
99	19.827	20.031	205	6	Gate 19 to 25	
100	20.032	20.192	161	6	Gate 25 to 31	
101	20.193	20.284	92	6	Gate 31 to 35	
102	20.285	20.566	282	6	Gate 35 to 43	
103	20.567	20.837	271	6	Gate 43 to 50	
104	20.838	20.951	114	6	Gate 50 to 55	
105	20.952	21.214	263	6	Gate 55 to 60	
106	21.215	21.272	58		Finish	
107	21.273	21.338	66		Winner's Box	
108	21.339	21.418	80		Finish	
109	21.419	21.443	25		FIS Wipe	
110	21.444	21.736	293			Repetition
111	21.737	21.756	20		FIS Wipe	
112	21.757	21.844	88		Start Preparation	
113	21.845	22.030	186		Start House	
114	22.031	22.280	250	7	Gate 01 to 07	
115	22.281	22.600	320	7	Gate 07 to 19	

116	22.601	22.781	181	7	Gate 19 to 25	
117	22.782	22.964	183	7	Gate 25 to 31	
118	22.965	23.054	90	7	Gate 31 to 35	
119	23.055	23.356	302	7	Gate 35 to 43	
120	23.357	23.600	244	7	Gate 43 to 50	
121	23.601	23.770	170	7	Gate 50 to 55	
122	23.771	23.982	212	7	Gate 55 to 60	
123	23.983	24.162	180		Finish	
124	24.163	24.185	23		FIS Wipe	
125	24.186	24.405	220			Repetition
126	24.406	24.426	21		FIS Wipe	
127	24.427	24.686	260		Start House	
128	24.687	24.791	105	8	Start Preparation	
129	24.792	24.989	198	8	Gate 01 to 07	
130	24.990	25.323	334	8	Gate 07 to 19	
131	25.324	25.473	150	8	Gate 19 to 25	
132	25.474	25.681	208	8	Gate 25 to 31	
133	25.682	25.827	146	8	Gate 31 to 35	
134	25.828	26.060	233	8	Gate 35 to 43	
135	26.061	26.315	255	8	Gate 43 to 50	
136	26.316	26.455	140	8	Gate 50 to 55	
137	26.456	26.729	274	8	Gate 55 to 60	
138	26.730	26.790	61		Stands	
139	26.791	26.911	121		Finish	
140	26.912	26.936	25		FIS Wipe	
141	26.937	27.130	194			Repetition
142	27.131	27.150	20		FIS Wipe	
143	27.151	27.234	84		Finish	
144	27.235	27.246	12		Dissolve	
145	27.247	27.330	84		Start Preparation	
146	27.331	27.513	183		Start House	
147	27.514	27.738	225	9	Gate 01 to 07	
148	27.739	28.087	349	9	Gate 07 to 19	
149	28.088	28.246	159	9	Gate 19 to 25	
150	28.247	28.443	197	9	Gate 25 to 31	
151	28.444	28.531	88	9	Gate 31 to 35	
152	28.532	28.856	325	9	Gate 35 to 43	
153	28.857	29.083	227	9	Gate 43 to 50	
154	29.084	29.250	167	9	Gate 50 to 55	
155	29.251	29.476	226	9	Gate 55 to 60	
156	29.477	29.511	35		Finish	
157	29.512	29.558	47		Winner’s Box	

158	29.559	29.768	210		Finish	
159	29.769	29.793	25		FIS Wipe	
160	29.794	30.034	241			Repetition
161	30.035	30.055	21		FIS Wipe	
162	30.056	30.199	144		Finish	
163	30.200	30.210	11		Dissolve	
164	30.211	30.491	281	10	Gate 01 to 07	
165	30.492	30.827	336	10	Gate 07 to 19	
166	30.828	31.000	173	10	Gate 19 to 25	
167	31.001	31.175	175	10	Gate 25 to 31	
168	31.176	31.266	91	10	Gate 31 to 35	
169	31.267	31.577	311	10	Gate 35 to 43	Mistake
170	31.578	31.828	251	10	Gate 43 to 50	
171	31.829	31.972	144	10	Gate 50 to 55	
172	31.973	32.225	253	10	Gate 55 to 60	
173	32.226	32.416	191		Finish	
174	32.417	32.440	24		FIS Wipe	
175	32.441	32.604	164			Repetition
176	32.605	32.619	15		Dissolve	
177	32.620	32.842	223			Repetition
178	32.843	32.862	20		FIS Wipe	
179	32.863	33.010	148		Start House	
180	33.011	33.083	73	11	Start Preparation	
181	33.084	33.263	180	11	Gate 01 to 07	
182	33.264	33.627	364	11	Gate 07 to 19	
183	33.628	33.774	147	11	Gate 19 to 25	
184	33.775	33.985	211	11	Gate 25 to 31	
185	33.986	34.078	93	11	Gate 31 to 35	
186	34.079	34.375	297	11	Gate 35 to 43	
187	34.376	34.640	265	11	Gate 43 to 50	
188	34.641	34.808	168	11	Gate 50 to 55	
189	34.809	35.024	216	11	Gate 55 to 60	
190	35.025	35.128	104		Finish	
191	35.129	35.152	24		FIS Wipe	
192	35.153	35.368	216			Repetition
193	35.369	35.388	20		FIS Wipe	
194	35.389	35.440	52		Finish	
195	35.441	35.597	157		Stands	
196	35.598	35.607	10		Dissolve	
197	35.608	35.767	160		Start House	
198	35.768	35.944	177	12	Gate 01 to 07	
199	35.945	36.342	398	12	Gate 07 to 19	

200	36.343	36.517	175	12	Gate 19 to 25	
201	36.518	36.657	140	12	Gate 25 to 31	
202	36.658	36.699	42	12	Gate 31 to 35	
203	36.700	36.721	22	12	Gate 35 to 43	Cutting Error
204	36.722	36.804	83	12	Gate 31 to 35	Back
205	36.805	37.116	312	12	Gate 35 to 43	
206	37.117	37.346	230	12	Gate 43 to 50	
207	37.347	37.499	153	12	Gate 50 to 55	
208	37.500	37.735	236	12	Gate 55 to 60	
209	37.736	37.882	147		Finish	
210	37.883	37.907	25		FIS Wipe	
211	37.908	38.137	230			Repetition
212	38.138	38.157	20		FIS Wipe	
213	38.158	38.208	51		Finish	
214	38.209	38.282	74		Winner's Box	
215	38.283	38.293	11		Dissolve	
216	38.294	38.546	253		Start House	
217	38.547	38.807	261	13	Gate 01 to 07	
218	38.808	39.133	326	13	Gate 07 to 19	
219	39.134	39.303	170	13	Gate 19 to 25	
220	39.304	39.497	194	13	Gate 25 to 31	
221	39.498	39.587	90	13	Gate 31 to 35	Mistake
222	39.588	39.908	321	13	Gate 35 to 43	
223	39.909	40.175	267	13	Gate 43 to 50	
224	40.176	40.292	117	13	Gate 50 to 55	
225	40.293	40.557	265	13	Gate 55 to 60	
226	40.558	40.717	160		Finish	
227	40.718	40.741	24		FIS Wipe	
228	40.742	40.949	208			Repetition
229	40.950	40.970	21		FIS Wipe	
230	40.971	41.025	55		Finish	
231	41.026	41.038	13		Dissolve	
232	41.039	41.186	148		Start House	
233	41.187	41.484	298	14	Gate 01 to 07	
234	41.485	41.835	351	14	Gate 07 to 19	
235	41.836	41.991	156	14	Gate 19 to 25	
236	41.992	42.194	203	14	Gate 25 to 31	
237	42.195	42.285	91	14	Gate 31 to 35	
238	42.286	42.577	292	14	Gate 35 to 43	
239	42.578	42.841	264	14	Gate 43 to 50	
240	42.842	43.006	165	14	Gate 50 to 55	
241	43.007	43.216	210	14	Gate 55 to 60	

242	43.217	43.352	136		Finish	
243	43.353	43.376	24		FIS Wipe	
244	43.377	43.565	189			Repetition
245	43.566	43.586	21		FIS Wipe	
246	43.587	43.672	86		Finish	
247	43.673	43.679	7		Dissolve	
248	43.680	43.781	102		Start Preparation	
249	43.782	44.018	237		Start House	
250	44.019	44.224	206	15	Gate 01 to 07	
251	44.225	44.595	371	15	Gate 07 to 19	
252	44.596	44.787	192	15	Gate 19 to 25	
253	44.788	44.953	166	15	Gate 25 to 31	
254	44.954	45.040	87	15	Gate 31 to 35	
255	45.041	45.386	346	15	Gate 35 to 43	Mistake
256	45.387	45.612	226	15	Gate 43 to 50	
257	45.613	45.733	121	15	Gate 50 to 55	
258	45.734	45.999	266	15	Gate 55 to 60	
259	46.000	46.206	207		Finish	
260	46.207	46.336	130		Winner’s Box	
261	46.337	46.360	24		FIS Wipe	
262	46.361	46.713	353			Repetition
263	46.714	46.733	20		FIS Wipe	
264	46.734	46.902	169		Finish	
265	46.903	46.919	17		Dissolve	
266	46.920	47.545	626			Standings
267	47.546	47.553	8		Dissolve	
268	47.554	47.674	121		Start Preparation	Repetition
269	47.675	47.682	8		Dissolve	
270	47.683	47.919	237			Repetition
271	47.920	47.927	8		Dissolve	
272	47.928	48.057	130		Finish	Repetition
273	48.058	48.066	9		Dissolve	
274	48.067	48.394	328		Gate 01 to 07	Repetition
275	48.395	48.402	8		Dissolve	
276	48.403	48.562	160			Repetition
277	48.563	48.570	8		Dissolve	
278	48.571	48.681	111		Finish	Repetition
279	48.682	48.689	8		Dissolve	
280	48.690	48.793	104		Start Preparation	Repetition
281	48.794	48.801	8		Dissolve	
282	48.802	48.955	154			Repetition
283	48.956	48.963	8		Dissolve	

284	48.964	49.049	86		Finish	Repetition
285	49.050	49.054	5		Dissolve	
286	49.055	49.150	96		Winner's Box	
287	49.151	49.168	18		Dissolve	
288	49.169	49.278	110		Start House	
289	49.279	49.462	184	16	Gate 01 to 07	
290	49.463	49.836	374	16	Gate 07 to 19	
291	49.837	49.994	158	16	Gate 19 to 25	
292	49.995	50.203	209	16	Gate 25 to 31	
293	50.204	50.329	126	16	Gate 31 to 35	
294	50.330	50.603	274	16	Gate 35 to 43	
295	50.604	50.863	260	16	Gate 43 to 50	
296	50.864	51.042	179	16	Gate 50 to 55	
297	51.043	51.253	211	16	Gate 55 to 60	
298	51.254	51.381	128		Finish	
299	51.382	51.391	10		Dissolve	
300	51.392	51.546	155		Start House	
301	51.547	51.763	217	17	Gate 01 to 07	
302	51.764	52.152	389	17	Gate 07 to 19	
303	52.153	52.287	135	17	Gate 19 to 25	
304	52.288	52.499	212	17	Gate 25 to 31	
305	52.500	52.600	101	17	Gate 31 to 35	
306	52.601	52.895	295	17	Gate 35 to 43	
307	52.896	53.158	263	17	Gate 43 to 50	
308	53.159	53.329	171	17	Gate 50 to 55	
309	53.330	53.552	223	17	Gate 55 to 60	
310	53.553	53.605	53		Stands	
311	53.606	53.758	153		Finish	
312	53.759	53.769	11		Dissolve	
313	53.770	53.957	188	18	Gate 01 to 07	
314	53.958	54.333	376	18	Gate 07 to 19	
315	54.334	54.496	163	18	Gate 19 to 25	
316	54.497	54.697	201	18	Gate 25 to 31	
317	54.698	54.807	110	18	Gate 31 to 35	
318	54.808	55.118	311	18	Gate 35 to 43	
319	55.119	55.355	237	18	Gate 43 to 50	
320	55.356	55.474	119	18	Gate 50 to 55	
321	55.475	55.740	266	18	Gate 55 to 60	
322	55.741	55.857	117		Finish	
323	55.858	55.866	9		Dissolve	
324	55.867	56.017	151		Start House	
325	56.018	56.249	232	19	Gate 01 to 07	

326	56.250	56.618	369	19	Gate 07 to 19
327	56.619	56.780	162	19	Gate 19 to 25
328	56.781	56.969	189	19	Gate 25 to 31
329	56.970	57.066	97	19	Gate 31 to 35
330	57.067	57.383	317	19	Gate 35 to 43
331	57.384	57.621	238	19	Gate 43 to 50
332	57.622	57.761	140	19	Gate 50 to 55
333	57.762	58.022	261	19	Gate 55 to 60
334	58.023	58.070	48		Stands
335	58.071	58.130	60		Finish
336	58.131	58.141	11		Dissolve
337	58.142	58.510	369	20	Gate 01 to 07
338	58.511	58.898	388	20	Gate 07 to 19
339	58.899	59.041	143	20	Gate 19 to 25
340	59.042	59.245	204	20	Gate 25 to 31
341	59.246	59.335	90	20	Gate 31 to 35
342	59.336	59.637	302	20	Gate 35 to 43
343	59.638	59.892	255	20	Gate 43 to 50
344	59.893	60.065	173	20	Gate 50 to 55
345	60.066	60.268	203	20	Gate 55 to 60
346	60.269	60.432	164		Finish
347	60.433	60.444	12		Dissolve
348	60.445	60.484	40		Start House
349	60.485	60.682	198	21	Gate 01 to 07
350	60.683	61.045	363	21	Gate 07 to 19
351	61.046	61.214	169	21	Gate 19 to 25
352	61.215	61.405	191	21	Gate 25 to 31
353	61.406	61.531	126	21	Gate 31 to 35
354	61.532	61.853	322	21	Gate 35 to 43
355	61.854	62.069	216	21	Gate 43 to 50
356	62.070	62.243	174	21	Gate 50 to 55
357	62.244	62.444	201	21	Gate 55 to 60
358	62.445	62.499	55		Stands
359	62.500	62.612	113		Finish
360	62.613	62.625	13		Dissolve
361	62.626	62.754	129		Start House
362	62.755	62.989	235	22	Gate 01 to 07
363	62.990	63.350	361	22	Gate 07 to 19
364	63.351	63.507	157	22	Gate 19 to 25
365	63.508	63.705	198	22	Gate 25 to 31
366	63.706	63.837	132	22	Gate 31 to 35
367	63.838	64.128	291	22	Gate 35 to 43

368	64.129	64.393	265	22	Gate 43 to 50	
369	64.394	64.529	136	22	Gate 50 to 55	
370	64.530	64.779	250	22	Gate 55 to 60	
371	64.780	64.960	181		Finish	
372	64.961	64.969	9		Dissolve	
373	64.970	65.609	640		Gate 01 to 07	Standings
374	65.610	65.619	10		Dissolve	
375	65.620	65.712	93		Start Preparation	Repetition
376	65.713	65.720	8		Dissolve	
377	65.721	65.887	167			Repetition
378	65.888	65.895	8		Dissolve	
379	65.896	66.032	137		Finish	Repetition
380	66.033	66.040	8		Dissolve	
381	66.041	66.192	152		Gate 01 to 07	Repetition
382	66.193	66.201	9		Dissolve	
383	66.202	66.453	252			Repetition
384	66.454	66.461	8		Dissolve	
385	66.462	66.585	124		Finish	Repetition
386	66.586	66.593	8		Dissolve	
387	66.594	66.711	118		Start Preparation	Repetition
388	66.712	66.719	8		Dissolve	
389	66.720	66.953	234			Repetition
390	66.954	66.961	8		Dissolve	
391	66.962	67.078	117		Finish	Repetition
392	67.079	67.085	7		Dissolve	
393	67.086	67.167	82		Winner's Box	
394	67.168	67.192	25		Dissolve	
395	67.193	67.297	105		Finish	
396	67.298	67.323	26		Dissolve	
397	67.324	67.394	71		Forest	
398	67.395	67.421	27		Dissolve	
399	67.422	67.609	188		Gate 01 to 07	
400	67.610	67.622	13		Dissolve	
401	67.623	67.872	250		Start Preparation	
402	67.873	68.248	376	23	Gate 01 to 07	
403	68.249	68.610	362	23	Gate 07 to 19	Mistake
404	68.611	68.776	166	23	Gate 19 to 25	
405	68.777	68.971	195	23	Gate 25 to 31	
406	68.972	69.067	96	23	Gate 31 to 35	
407	69.068	69.431	364	23	Gate 35 to 43	Mistake
408	69.432	69.702	271	23	Gate 43 to 50	Mistake
409	69.703	69.832	130	23	Gate 50 to 55	

410	69.833	70.075	243	23	Gate 55 to 60
411	70.076	70.202	127		Finish
412	70.203	70.211	9		Dissolve
413	70.212	70.301	90		Start House
414	70.302	70.565	264	24	Gate 01 to 07
415	70.566	70.867	302	24	Gate 07 to 19
416	70.868	71.043	176	24	Gate 19 to 25
417	71.044	71.301	258	24	Gate 25 to 31
418	71.302	71.375	74	24	Gate 31 to 35
419	71.376	71.694	319	24	Gate 35 to 43
420	71.695	71.915	221	24	Gate 43 to 50
421	71.916	72.052	137	24	Gate 50 to 55
422	72.053	72.296	244	24	Gate 55 to 60
423	72.297	72.412	116		Finish
424	72.413	72.420	8		Dissolve
425	72.421	72.514	94		Start House
426	72.515	72.711	197	25	Gate 01 to 07
427	72.712	73.081	370	25	Gate 07 to 19
428	73.082	73.255	174	25	Gate 19 to 25
429	73.256	73.444	189	25	Gate 25 to 31
430	73.445	73.603	159	25	Gate 31 to 35
431	73.604	73.841	238	25	Gate 35 to 43
432	73.842	74.100	259	25	Gate 43 to 50
433	74.101	74.244	144	25	Gate 50 to 55
434	74.245	74.490	246	25	Gate 55 to 60
435	74.491	74.665	175		Finish
436	74.666	74.676	11		Dissolve
437	74.677	74.750	74		Start Preparation
438	74.751	75.094	344	26	Gate 01 to 07
439	75.095	75.426	332	26	Gate 07 to 19
440	75.427	75.645	219	26	Gate 19 to 25
441	75.646	75.792	147	26	Gate 25 to 31
442	75.793	75.897	105	26	Gate 31 to 35
443	75.898	76.205	308	26	Gate 35 to 43
444	76.206	76.478	273	26	Gate 43 to 50
445	76.479	76.591	113	26	Gate 50 to 55
446	76.592	76.842	251	26	Gate 55 to 60
447	76.843	76.991	149		Finish
448	76.992	77.000	9		Dissolve
449	77.001	77.257	257	27	Gate 01 to 07
450	77.258	77.565	308	27	Gate 07 to 19
451	77.566	77.750	185	27	Gate 19 to 25

452	77.751	77.967	217	27	Gate 25 to 31	
453	77.968	78.087	120	27	Gate 31 to 35	
454	78.088	78.409	322	27	Gate 35 to 43	
455	78.410	78.614	205	27	Gate 43 to 50	
456	78.615	78.766	152	27	Gate 50 to 55	
457	78.767	79.004	238	27	Gate 55 to 60	
458	79.005	79.151	147		Finish	
459	79.152	79.159	8		Dissolve	
460	79.160	79.311	152		Start House	
461	79.312	79.521	210	28	Gate 01 to 07	
462	79.522	79.873	352	28	Gate 07 to 19	
463	79.874	80.101	228	28	Gate 19 to 25	
464	80.102	80.245	144	28	Gate 25 to 31	
465	80.246	80.347	102	28	Gate 31 to 35	
466	80.348	80.635	288	28	Gate 35 to 43	
467	80.636	80.898	263	28	Gate 43 to 50	
468	80.899	81.047	149	28	Gate 50 to 55	
469	81.048	81.301	254	28	Gate 55 to 60	
470	81.302	81.424	123		Finish	
471	81.425	81.433	9		Dissolve	
472	81.434	82.121	688	29	Gate 01 to 07	
473	82.122	82.283	162	29	Gate 07 to 19	
474	82.284	82.481	198	29	Gate 19 to 25	
475	82.482	82.590	109	29	Gate 25 to 31	Mistake
476	82.591	82.952	362		Gate 31 to 35	Out
477	82.953	82.977	25		FIS Wipe	
478	82.978	83.156	179		Gate 31 to 35	Repetition
479	83.157	83.199	43		Black Screen	
480	83.200	83.219	20		FIS Wipe	
481	83.220	83.450	231		Gate 31 to 35	Out
482	83.451	83.459	9		Dissolve	
483	83.460	83.529	70		Start Preparation	
484	83.530	83.787	258		Start House	
485	83.788	84.022	235	30	Gate 01 to 07	
486	84.023	84.341	319	30	Gate 07 to 19	
487	84.342	84.513	172	30	Gate 19 to 25	
488	84.514	84.737	224	30	Gate 25 to 31	
489	84.738	84.889	152	30	Gate 31 to 35	
490	84.890	85.141	252	30	Gate 35 to 43	
491	85.142	85.391	250	30	Gate 43 to 50	
492	85.392	85.649	258	30	Gate 50 to 55	
493	85.650	86.028	379	30	Finish	

494	86.029	86.050	22	Dissolve	
495	86.051	86.658	608		Standings

Cut Detector Metrics by Threshold

Threshold	C	F	M	R	P	Q	F1
0	306	84893	0	1	0,0036	0,0036	0,0072
1	306	81399	0	1	0,0037	0,0037	0,0075
2	306	75831	0	1	0,004	0,004	0,008
3	306	67017	0	1	0,0045	0,0045	0,009
4	306	58549	0	1	0,0052	0,0052	0,0103
5	306	50748	0	1	0,006	0,006	0,0119
6	306	43453	0	1	0,007	0,007	0,0139
7	306	36220	0	1	0,0084	0,0084	0,0166
8	306	29688	0	1	0,0102	0,0102	0,0202
9	305	24252	1	0,9967	0,0124	0,0124	0,0245
10	305	19648	1	0,9967	0,0153	0,0153	0,0301
11	303	15619	3	0,9902	0,019	0,019	0,0373
12	300	12350	6	0,9804	0,0237	0,0237	0,0463
13	299	9575	7	0,9771	0,0303	0,0303	0,0587
14	298	7377	8	0,9739	0,0388	0,0388	0,0747
15	296	5705	10	0,9673	0,0493	0,0492	0,0939
16	294	4409	12	0,9608	0,0625	0,0624	0,1174
17	291	3508	15	0,951	0,0766	0,0763	0,1418
18	289	2911	17	0,9444	0,0903	0,0898	0,1649
19	287	2418	19	0,9379	0,1061	0,1054	0,1906
20	285	2056	21	0,9314	0,1217	0,1207	0,2153
21	278	1808	28	0,9085	0,1333	0,1315	0,2324
22	276	1598	30	0,902	0,1473	0,145	0,2532
23	274	1436	32	0,8954	0,1602	0,1573	0,2718
24	272	1318	34	0,8889	0,1711	0,1675	0,2869
25	269	1195	37	0,8791	0,1837	0,1792	0,304
26	267	1066	39	0,8725	0,2003	0,1946	0,3258
27	265	927	41	0,866	0,2223	0,2149	0,3538
28	260	839	46	0,8497	0,2366	0,2271	0,3701
29	256	732	50	0,8366	0,2591	0,2466	0,3957
30	247	664	59	0,8072	0,2711	0,2546	0,4059
31	236	574	70	0,7712	0,2914	0,2682	0,4229
32	230	516	76	0,7516	0,3083	0,2798	0,4373
33	216	437	90	0,7059	0,3308	0,2907	0,4505
34	211	355	95	0,6895	0,3728	0,3192	0,4839

35	203	274	103	0,6634	0,4256	0,35	0,5185
36	191	216	115	0,6242	0,4693	0,3659	0,5358
37	186	162	120	0,6078	0,5345	0,3974	0,5688
38	174	118	132	0,5686	0,5959	0,4104	0,5819
39	158	71	148	0,5163	0,69	0,4191	0,5907
40	148	44	158	0,4837	0,7708	0,4229	0,5944
41	141	30	165	0,4608	0,8246	0,4196	0,5912
42	127	15	179	0,415	0,8944	0,3956	0,567
43	117	8	189	0,3824	0,936	0,3726	0,5429
44	106	5	200	0,3464	0,955	0,3408	0,5084
45	96	4	210	0,3137	0,96	0,3097	0,4729
46	88	3	218	0,2876	0,967	0,2848	0,4433
47	76	2	230	0,2484	0,9744	0,2468	0,3958
48	73	1	233	0,2386	0,9865	0,2378	0,3842
49	68	1	238	0,2222	0,9855	0,2215	0,3627
50	63	0	243	0,2059	1	0,2059	0,3415
51	59	0	247	0,1928	1	0,1928	0,3233
52	58	0	248	0,1895	1	0,1895	0,3187
53	49	0	257	0,1601	1	0,1601	0,2761
54	45	0	261	0,1471	1	0,1471	0,2564
55	43	0	263	0,1405	1	0,1405	0,2464
56	38	0	268	0,1242	1	0,1242	0,2209
57	34	0	272	0,1111	1	0,1111	0,2
58	33	0	273	0,1078	1	0,1078	0,1947
59	28	0	278	0,0915	1	0,0915	0,1677
60	27	0	279	0,0882	1	0,0882	0,1622

Da Vinci Resolve Metrics

Specs	C	F	M	R	P	Q	F1
All transitions	627	111	1100	0,3631	0,8496	0,3411	0,5087
Cuts only	298	262	8	0,9739	0,5321	0,5246	0,6882

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