No more Autobahn! Scenic Route Generation Using Googles Street View

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ABSTRACT
Navigation systems allow drivers to find the shortest or fastest path between two or multiple locations mostly using time or distance as input parameters. Various researchers extended traditional route planning approaches by taking into account the user's preferences, such as enjoying a coastal view or alpine landscapes during a drive. Current approaches mainly rely on volunteered geographic information (VGI), such as point of interest (POI) data from OpenStreetMap, or social media data, such as geotagged photos from Flickr, to generate scenic routes. While these approaches use proximity, distribution or other spatial relationships of the data sets, they do not take into account the actual view on specific route segments. In this paper, we propose *Autobahn*: a system for generating scenic routes using Google Street View images to classify route segments based on their visual characteristics enhancing the driving experience. We show that this vision-based approach can complement other approaches for scenic route planning and introduce a personalized scenic route by aligning the characteristics of the route to the preferences of the user.

ACM Classification Keywords
H.5.m Information interfaces and presentation: Miscellaneous

Author Keywords
Deep Learning; Intelligent User Interfaces, Google Street View; Scenic Routes

INTRODUCTION & RELATED WORK
The rapid development of autonomous vehicles will also radically change the way we perceive the in-car experience [5]. Navigation will no longer be only a tool to navigate from point *A* to point *B* on the shortest or fastest path, but the selection of a route will have an impact on the in-car experience as well. This is already true for travellers and owners of convertibles or motorbikes as the driving itself has an intrinsic motivation for them [1].

There is already a large corpus of related work that explores the generation of scenic or alternatives routes. For example, Hochmair et al. [1, 4] describe an approach to generate scenic routes using different sources of volunteered geographic information (VGI) and data from photo sharing platforms. The *GPSView* system uses a similar approach and adapts an attention-aware technique to community contributed photos and allows travellers to enjoy sightseeing during a trip [13]. As shown by Bolzoni et al. [2], adding category information to points of interest (POIs) makes it easier for tourists to formulate their preferences while planning an itinerary. In order to provide a better navigation experience, Samsonov et al. [10] proposed that navigation systems should also be aware of so-called space usage rules (such as no-swimming signs, no-surfing signs or no-fishing signs) to be able to guide the users to places where they can enjoy certain activities (e.g. swimming or fishing). In the domain of pedestrian navigation multiple applications and research prototypes exist to improve walking experiences. The application *Space Recommender System* [11] merges data from social networks to improve walking experiences in urban spaces, whereas the *Hobbit* application [8] helps people to avoid company in rural areas.

While all these approaches provide interesting alternatives to the shortest or fastest route, the main limitation is that these techniques do not consider the actual view from the road and rely on other data to judge the route's aspects. It has been shown that in order to improve driver experience, it is necessary to take into account a rich set of visual landscape features. For example, Qin et al. [9] showed that the presence of billboards negatively influences scenic qualities and the presence of lakes positively improves the overall driving experience. One could also consider a scenario where a street, that is close to the shoreline, might be directly behind dams, or the view on the ocean is blocked by houses, tunnels or trees (as illustrated in Figure 1). On the other hand, a street further away from the coast might offer a beautiful view over the ocean (e.g. because there is a high plateau). In addition, VGI could also be biased [3] or not uniformly distributed and affect other approaches for scenic route generation. For exam-

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Figure 1. By looking on the map of a route near Copenhagen on the left, a user would expect view from the ocean from all locations, but most of the time it is blocked by trees or wastelands. On the left: The route, and the computed grid. In the middle: the corresponding GSV images. On the right: the outcome of the classification. The categories with the highest probability p are assigned to each grid cell. Image and base map ©Google 2015.

ple, while there will be a high amount of geo-tagged photos taken around a popular sight, it is unlikely that this location will be visible from the road. While these limitations could be overcome by creating a detailed 3D model of the environment and applying scene and visibility analysis [12], such an approach would be computationally very expensive on a global scale. However, it would also not take into account the presence of flora, e.g. trees and bushes, at a location.

To overcome these issues, we propose a pipeline to generate scenic routes based on Google Street View (GSV) data. Our automated system named *Autobahn* crawls GSV images alongside routes and tags and classifies these images using deep learning [7]. In contrast to other photo sharing platforms, building upon GSV has the advantage that these images are taken from a vehicle (in the majority of the cases) on major roads. We provide insights on the technical implementation, as well as a first user study, that compares our approach with the state-of-the-art.

THE AUTOBAHN PIPELINE

Typical automotive navigation between two locations requires a starting point, a destination and routing parameters such as fastest or shortest route. As input, the *Autobahn* system requires the user to additionally select one of the 6 predefined scenic routing parameters in order to align the routing to the user's preferences. An overview on the developed components can be seen in Figure 2. The following sections explain the main components of the pipeline in detail.

Grid Creation

When starting a route generation between two locations, the bounding box of the area is taken as the reference grid for our calculations. The corresponding OpenStreetMap (OSM) data of this area is downloaded through the OSM Overpass API. The area is divided into a grid with cells of one square kilometer size. The cell size corresponds to roughly one-minute driving time, assuming an average speed of 60 km per hour.

For each cell, one location is determined by selecting the closest road to the center of the cell. Roads classified as service roads in OSM are excluded as it is highly unlikely that GSV is available on these roads. If a cell does not contain any applicable roads, it will not be processed any further.

Street View Data Collection

In the next step, we generate panoramic images for all sample locations of the grid using GSV. As the GSV API does not allow to retrieve an entire panoramic view as a single image, we reconstruct the panorama by individually downloading image tiles and stitching them together. We iterate through the panorama with a pitch ranging from minus ten to seventy degrees in steps of ten degrees for each 10 degree heading in the 360 degree panoramic image. The resulting 288 images with a resolution of 640×640 pixels are then downscaled to 320×320 pixels. As the positions of all 288 tiles are known, the stitching process is straightforward and a single image of 11520×2560 pixels is generated. As the classification component (described in the next section) is trained on smaller pictures, we scaled panoramic image down by 80%. Figure 1 shows examples of the used 2304×512 pixel panoramas.

Panorama Classification

In order to classify the images, we used the pre-trained neural network created by Zhou et al. [14]. They used crowd workers to assign place tags to different images. This resulted in 205 place categories, such as field, forest, airport terminal or boat deck. The neural network was trained with 2,448,873 images of the ImageNet Database and showed an accuracy 50% on the evaluation dataset and even better results for other datasets, like the easier dataset SUN 205 (66.5% accuracy).

For classifying our panoramic images, we used the Caffe Deep Learning Framework for neural networks [6]. As our use case does simply require a distinction between a few unique place categories, tags related to indoor scenes were discarded.

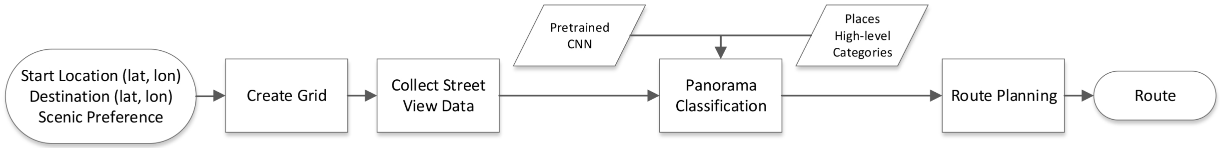

Figure 2. The *Autobahn* pipeline for scenic route generation using GSV images.

In an iterative process, we grouped the 111 trained scenes into 5 high-level scenic categories, namely *sightseeing* (e.g. viaduct, temple, amusement park), *nature and woods* (e.g. valley, alley, garden), *fields* (e.g. wheat field, corn field), *water* (e.g. ocean, harbor, coast) and *mountain* (e.g. butte, snowy mountain, volcano). The sixth category contained all non-scenic tags (e.g. *street*, *industry* and *building*). For each panoramic image, the neural network gives a probability what kind of landscape is most likely visible in the image. We categorized the images based on the category with the highest probability. The most probable tags for three examples on a route in Copenhagen are shown in the Figure 1 . We also list all the probabilities for the place classification and the category it belongs to. Three example outputs for a colored grid (with the corresponding categories) based on the panorama classifications can be seen in Figure 4 .

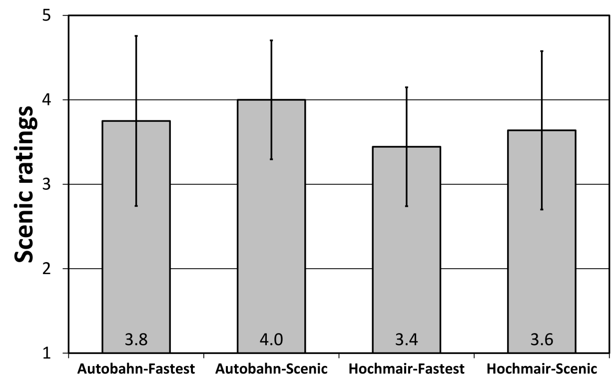

Figure 3. Mean values for a 5-point Likert scale (5=very scenic, 1=not scenic) ratings, error bars indicate standard deviation. Comparing two routes generated by the *Autobahn* system (*Autobahn*-scenic) and the fasted routes from the same start and end points (*Autobahn*-fastest). Same for the routes by Hochmair.

Route Planning

Once a region of interest (ROI) is classified based on the panoramic GSV image, we are able to plan different routes through the ROI. Our algorithm generates a scenic route from a given start point to a finish point through multiple or even all cells containing the scenic qualities constrained to the maximum travel time as selected by a user. For example, a user interested in *mountain views* would start by providing the system with his preference, a start location, a destination, and maximum travel time. The system provides the user with a personalized route in the ROI, maximizing the number of cells classified as *mountain* in the given time.

Since routing is not the main contribution of the paper, we implemented a first approach in two steps. Firstly, a route is created from the given start location to the destination while passing through the scenic cell surrounded by the most other scenic cells. In the second step, we recursively split existing segments by adding the closest scenic point to the route, as long as the overall route length does not exceed the value defined by the user or all points from the grid are added. If adding a point leads to going on a road twice, it is skipped. This routing strategy ensures a high concentration of the scenic preferences, while avoiding there-and-back detours. For routing from *A* to *B* in the algorithm, we used OpenRouteService[1] for the European routes and GraphHopper[2] for the USA routes.

RESULTS & EVALUATION

We have used our *Autobahn* system to classify GSV images in 10 different ROIs of about 32,000 km^2 around the world. Based on their preferences, users are able to plan various scenic routes throughout these 10 areas. An overview can be seen in Figure 4 . The grid view provides an overview of the classified area and provides insight into the generation of scenic routes. In the left image, showing the classification of Malloca, Spain, the following area classifications are visible: cities, fields and areas where a driver could enjoy nice mountain views. We have also classified the main highway system of Belgium, to provide users with an overview on the most scenic parts of the highways system. The interactive website can be accessed at `http://autobahn.edm.uhasselt.be`.

To further evaluate the *Autobahn* system, an online survey was conducted. Three different areas with scenic views were evaluated (Mallorca, Spain; Rhone-Alpes, France; Santa Barbara, USA). For each area, two routes with identical start and finish locations, were created. One route was generated using a default fastest route planning algorithm. The second route took into account the scenic information from our *Autobahn* system. The scenic routes were generated using the *mountain* and *water* tags, this because we expected users to pay more attention to sea and mountain views compared to forests, sightings and fields. In order to compare these results to previous work, we used three routes generated by Hochmair. et al. [1] and their fastest routing alternatives connecting the identical start and finish locations. These routes are located throughout the state of Florida (North Tampa, Odessa and Yankeetown). Each route contains one point every 100 to 500 meters, in average 34 points per route, and variated

[1]`http://openrouteservice.org`
[2]`http://graphhopper.com`

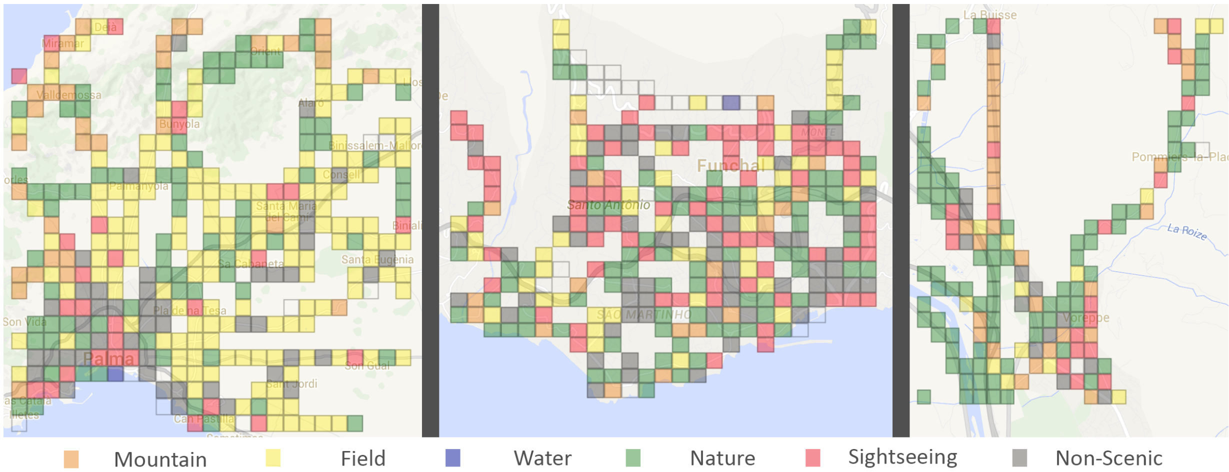

Figure 4. Three example colored grid outputs of *Autobahn*. From the left to the right: Mallorca (Spain), Madeira (Portugal), Rhone-Alpes (France). Base map: ©Google 2015

from 4.8 km to 16.4 km in distance. Both our routes and the routes of Hochmair shared same characteristics in terms of length and ratio between the scenic route and the fastest path. The routes were presented in Latin square order to prevent influences. For each route, the points on that route were sequentially iterated though. For each point, participants were shown the panoramic view on that location for a duration of two seconds. These images are not identical to the ones used for categorizing the grid. After each route, participants were asked to rate that route on a 5-point Likert scale with regard to the scenic qualities. They were also asked if they would like to travel the route in real-life. Participants were able to provide feedback on, why assessed a route scenic or not scenic in a free-text field. The survey took about 30-40 minutes to complete. A total of 24 participants (10 female, 14 male) were unfamiliar with the selected ROI and completed the survey. Participants ranged between 18 and 49 years old ($M = 32.4$, $SD = 9.2$), 18 owned a car and one owned a motorbike. Participants expressed preference to routes generated by the *Autobahn* system, as can be seen in Figure 3 . However a pair-wise comparison of these both results yields no significant differences. The routes generated by Hochmair were also preferred to the fastest routes, again with no significant difference. The free-text field answers revealed similar preferences toward the scenic routes. Participants commented “this is a mountain tour on an island”, “nature” and “a lot of greenery” for both the fastest and the scenic routes, but the more subjective answers also expressed a tendency towards the scenic routes, e.g. “nice, cool, beautiful, interesting”, compared to “boring and normal” for the fastest path. Participants also expressed overall positive feedback in the general idea behind the *Autobahn* system and were interested in the application for future use.

DISCUSSION & CONCLUSION

In this paper, we presented a novel approach to generate scenic routes based on automatic scene classification using GSV images. We created an automated pipeline that allows the user to define scenic preferences for a routing assignment from a given start location to a destination point. Our pipeline classifies regions using a deep learning into 6 different scenic categories. They are used to align the routing to the preferences of the user. Our results are promising as they visualize the diversity of scenic qualities in a selected region and reveal route qualities that go beyond those currently picked up by comparable systems such as Hochmair et al. [1]. Initial user tests revealed preferences to our routes generated by the *Autobahn* system compared to the fastest path, yet no statistical differences were found. As such ratings are highly subjective and might be influenced by several factors, we believe that the *Autobahn* system provides the first steps into scenic routes generation based on automatic scene classification using GSV images.

One could also imagine various other routing algorithms based on the classified GSV images. Users interested in diversity could be provided with a route through a region which contains a multitude of different scenic qualities. Alternatively, a route could be designed to ensure a highly diverse landscape or, on the contrary, a very monotone drive. Besides scenic routing, we believe the power of classifying GSV data has yet to be fully exploited in a diverse range of applications. As GSV images is constrained to mainly North America and Europe, our system is limited in this regard and lacks coverage in large parts of Asia, Africa and South-America, as well as major cities of Germany and Austria.

As our system can recommend routes with a large variety of different views, we believe that it can complement other approaches for scenic route planning. This will be further explored in the future. The generated grids can be used in regional statistics, such as cross referencing the scenic qualities of regions to health and population related data.

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REFERENCES

1. Majid Alivand, Hartwig Hochmair, and Sivaramakrishnan Srinivasan. 2015. Analyzing how travelers choose scenic routes using route choice models. *Computers, Environment and Urban Systems* 50 (2015), 41–52.
2. Paolo Bolzoni, Sven Helmer, Kevin Wellenzohn, Johann Gamper, and Periklis Andritsos. 2014. Efficient Itinerary Planning with Category Constraints. In *Proceedings of the 22Nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (SIGSPATIAL '14)*. 203–212.
3. Brent Hecht and Monica Stephens. 2014. A tale of cities: Urban biases in volunteered geographic information. *Proc. of ICWSM* (2014).
4. Hartwig Hochmair. 2010. Spatial Association of Geotagged Photos with Scenic Locations. *Geospatial Crossroads@ GI_Forum* 10 (2010), 91–100.
5. Hillary Page Ive, Wendy Ju, and Kirstin Kohler. 2014. Quantitative Measures of User Experience in Autonomous Driving Simulators. In *Adjunct Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI '14)*. 1–3.
6. Yangqing Jia, Evan Shelhamer, Jeff Donahue, Sergey Karayev, Jonathan Long, Ross Girshick, Sergio Guadarrama, and Trevor Darrell. 2014. Caffe: Convolutional Architecture for Fast Feature Embedding. *arXiv preprint arXiv:1408.5093* (2014).
7. Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. 2012. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*. 1097–1105.
8. Maaret Posti, Johannes Schöning, and Jonna Häkkilä. 2014. Unexpected journeys with the HOBBIT: the design and evaluation of an asocial hiking app. In *Proceedings of the 2014 conference on Designing interactive systems*. ACM, 637–646.
9. Xiaochun Qin, Michael J Meitner, Brent Chamberlain, and Xiaoning Zhang. 2008. Estimating visual quality of scenic highway using GIS and landscape visualizations. In *ESRI Users Conference*.
10. Pavel Andreevich Samsonov, Brent Hecht, and Johannes Schöning. 2015. From Automatic Sign Detection To Space Usage Rules Mining For Autonomous Driving. In *CHI 2015 Workshop on Experiencing Autonomous Vehicles: Crossing the Boundaries between a Drive and a Ride*. ACM.
11. Martin Traunmueller, Ava Fatah gen Schieck, Johannes Schöning, and Duncan Brumby. 2013. The path is the reward: considering social networks to contribute to the pleasure of urban strolling. In *CHI'13 Extended Abstracts on Human Factors in Computing Systems*. ACM, 919–924.
12. Jianwei Zhang, Hiroshi Kawasaki, and Yukiko Kawai. 2008. A Tourist Route Search System Based on Web Information and the Visibility of Scenic Sights. In *Second International Symposium on Universal Communication, 2008 (ISUC '08)*. 154–161.
13. Yan-Tao Zheng, Shuicheng Yan, Zheng-Jun Zha, Yiqun Li, Xiangdong Zhou, Tat-Seng Chua, and Ramesh Jain. 2013. GPSView: A Scenic Driving Route Planner. *ACM Trans. Multimedia Comput. Commun. Appl.* 9, 1, Article 3 (Feb. 2013), 18 pages.
14. Bolei Zhou, Agata Lapedriza, Jianxiong Xiao, Antonio Torralba, and Aude Oliva. 2014. Learning deep features for scene recognition using places database. In *Advances in Neural Information Processing Systems*. 487–495.