Analysis of Topographic Maps for Recreational Purposes using Decision Trees

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***Abstract*—In this paper we describe a method for predicting the subjective quality of a new mountain bike route for a particular subject based on routes previously ridden and ranked by the subject. GPS tracks of the previously ridden routes are over laid on rasterized topographic maps and topographic features are extracted in the vicinity of the routes using image processing techniques. The subject ranks each previously ridden route segment on four subjective qualities. The extracted topographic features and the subjective rankings are used as input vectors and target vectors to train a series of decision trees. The decision trees are then tested on a series of route segments not used in the decision tree training. The decision trees were able to exactly predict the subjective rankings with over 60% accuracy vs. 20% accuracy for random selection. When close matches are allowed in the prediction of subjective ranking (plus or minus one point vs. actual) the accuracy of the decision trees increased to 90% and above.**

Keywords—topographic maps; decision trees; recreation; machine learning; mountain bike; route selection; GPS

I. Introduction

The majority of people who enjoy outdoor recreational activities have access to portable GPS devices [1], either in their mobile phone or a stand-alone device. GPS manufacturers and smart phone application developers use this capability to provide outdoor recreational users with means of creating traces of their routes that can be laid on top of rasterized topographic maps like MapSource [2] or integrated into online mapping services like Google Earth [3]. Several iPhone applications designed for cyclists [4, 5] extract training information like distance traveled, elevation gained and lost, average speed and top speed in an attempt to characterize routes. However, most topographic map features (e.g., vegetation, road size, water features, isolation, etc.) that characterize the subjective quality of a route, are not utilized.

The goal of this paper is to present a method that predicts the suitability of mountain bike routes to a particular subject based on a set of subjective rankings by that subject on previously ridden routes. This is done by extracting topographic map features in the vicinity of a GPS created route and training decision trees [6, 7] to predict the user's subjective rankings of the route based on the map features. Estimated subjective rankings of new routes are then computed using the previously trained decision trees and GPS coordinates of the new route of interest to the user.

The following topographic features are used: water features, road size, contours, vegetation, and altitude variations. The user preferences being studied are: aesthetic nature of route, difficulty of route, adventurousness of route, overall enjoyment of route. Fig. 1 is an image of one of the map segments used to train and test the decision tree. The route highlighted in yellow is a GPS track captured on a Garmin etrex Legend HCs handheld GPS and overlaid on a topographic map using Garmin's MapSource software. For more on extracting geographic features from raster maps, see [10, 11, 12].

II. Method

Our objective is to predict the suitability of mountain bike routes to a particular subject based on a set of subjective rankings by that subject on routes previously ridden by that subject. The results are a personalized predictor of route suitability for that particular subject.

The primary tool we used to predict the suitability is the decision tree. The decision tree is a well studied machine learning technique that has the advantage of being computationally low cost to create and even lower cost $\mathcal{O}$(log N) to use. However, decision trees require that the inputs (map features) and outputs (subjective preferences) be coded mathematically. For our problem this starts with the collection of route data and subjective preference rankings. The route data then has to be coded mathematically in a way that can be used as an input vector to a decision tree. Our methodology follows these steps:

- Capture route using GPS
- Generate subjective rankings by route segment
- Extract features from rasterized topographic maps
- Mathematically code features as attribute vectors
- Train the decision tree
- Test the decision tree

Each step of the methodology will now be described in further detail.

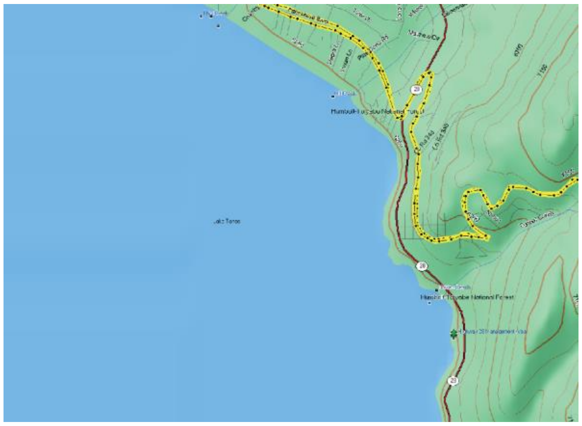

Fig. 1. Sample Map Segment with GPS Route

A. Route Capture

Five routes, were ridden by the test subject who carried a Garmin etrex Legend HCs handheld GPS. The GPS track was downloaded to Garmin's MapSource software which displays a topographic map of the route with the GPS track highlighted in yellow. The routes were then broken down into twenty route segments based on topography (each segment was had similar topographic features). The twenty segments were then exported as image files.

B. Subjective user rankings

After each ride, the subject was asked to rank each segment on four qualities: aesthetic nature, difficulty, adventurousness, overall enjoyment. Definitions for these qualities were not provided to the subject as the decision tree is intended to be subject specific (each rider will have their own decision tree that predicts which routes that rider will enjoy). The rankings are on a 1 to 5 scale with 1 being low and 5 being high.

C. Extraction of Features from Rasterized Topographic maps

Topographic map features are encoded in color. The colors vary within a range and overlapping features cause color variation which manifests itself as noise. However, color based feature extraction produces usable groupings of map features [8]. The following algorithm was used to extract specific features:

- For each pixel *i, j* in image of topographic map:
  - if pixel *i, j* falls within color range defined:
    - ⇨ do nothing
  - else
    - ⇨ set each pixel *i, j* to zero
- Repeat for all pixels in image

Table I shows the color ranges used to extract each type of feature. Figures 2 through 7 are the resulting sample maps segmented on these features.

TABLE I. COLOR CODING OF FEATURES OF INTEREST

	RGB Color Range		
	Red	***Green***	***Blue***
Large water feature	117 +/-20	182 +/-20	192 +/-20
Light duty roads	126 +/-50	126 +/-30	127 +/-30
Streams	55 +/-25	125 +/-25	192 +/-50
Highways	237+19/-50	32 +50/-32	36 +50/-36
Contour lines	184 +/-20	148 +/-20	103 +/-20
South facing slopes	84 +/-20	168 +/-20	117 +/-20
North and level slopes	150 +/-25	209 +/-25	169 +/-25

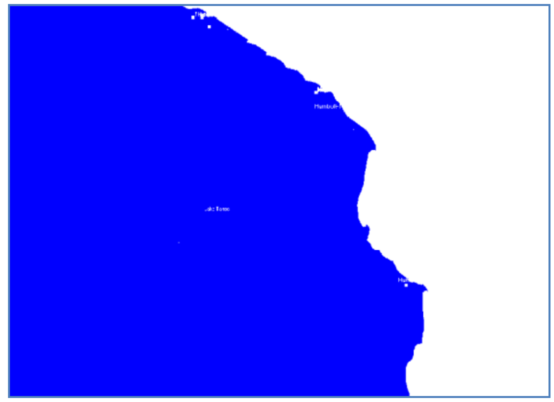

Fig. 2. Large water feature

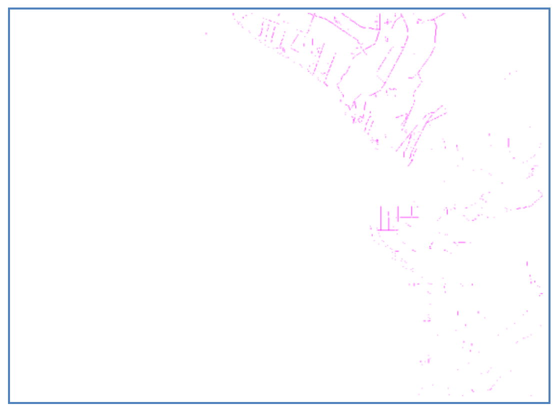

Fig. 3. Light Duty Roads

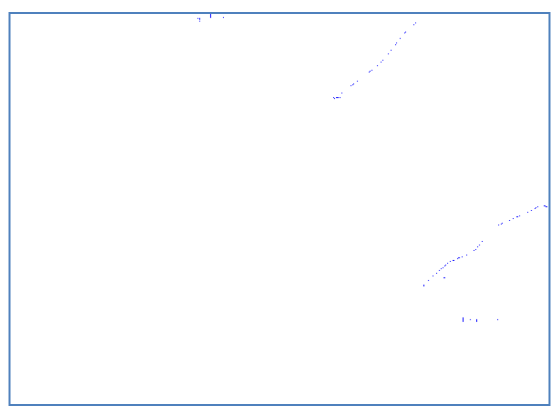

Fig. 4. Streams

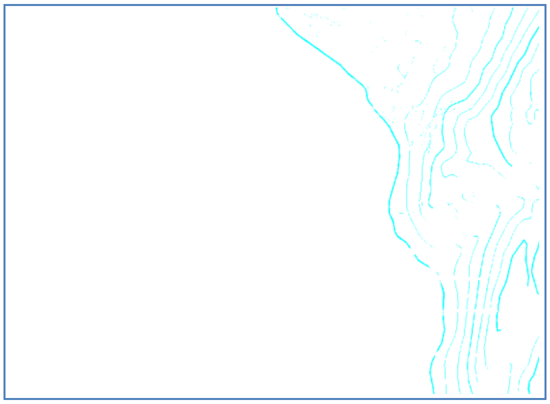

Fig. 5. Contour Lines

Fig. 6. South Facing Slopes

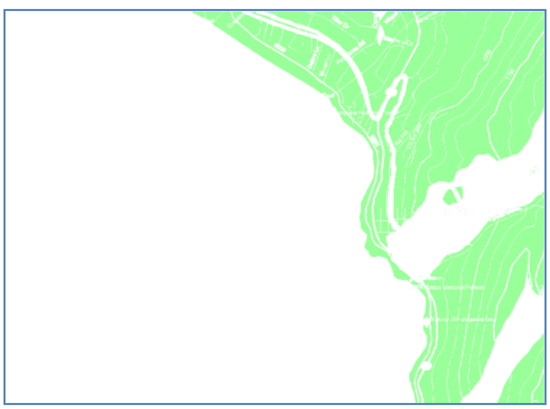

Fig. 7. Flat and North facing slopes

D. *Creating the Attribute Vectors for Decision Trees*

The terrain features that are of interest to mountain bike riders are typically a short distance from the route. Route masks were created using a circular spatial filter [9] with a radius of 50 pixels centered on the color of the GPS track. The algorithm used for creating the route mask is:

- Create mask equal to size of image (*mxn*)
- Initialize each pixel *i, j* of mask to zero
- For each pixel *i, j* in image of topographic map:
  - If pixel *i, j* is on the route:
    - ⇨ Center circular filter at *i, j* on mask
    - ⇨ Set each pixel in mask that falls within circular filter to 1
- Repeat for all pixels in image

To use the mask, the image with the feature or features of interest is logically ANDed with the mask. This produces an image that only has the feature of interest in the vicinity of the route. Fig. 8 shows the route mask created with the above algorithm logically ANDed with the original topographic map segment.

Once the image is masked and the feature of interest extracted, the importance of a given feature is calculated using equation 1.

$$I = P_f/(P_{nb}/d) \quad (1)$$

where I is the feature importance expressed in percent of total pixels in mask, P_f is the number of pixels in the masked area of the feature of interest, P_{nb} is the total number of pixels in the mask area, and d is the diameter of the circular mask.

The feature importance was then binned per the values in Table II and Table III. The binned values for the 20 map segments is the input feature vector for the decision tree.

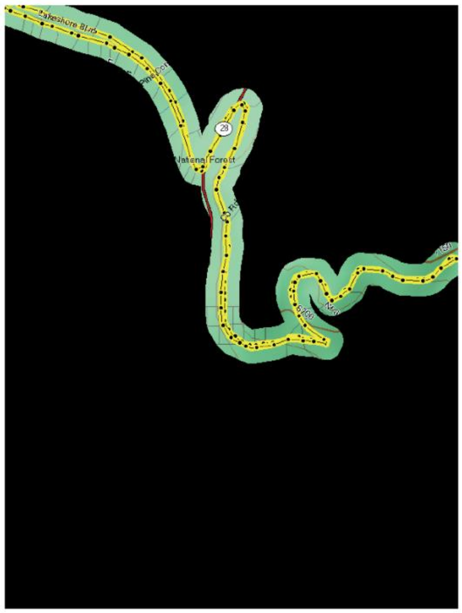

Fig. 8. Route Mask Created with Circular Filter

TABLE II. VALUES USE TO BIN FEATURE FOR FIRST FOUR FEATURES

Bin Value	Feature type			
	Large Water Feature	***Small Roads***	***Large Roads***	***Streams***
1	<2%	<.25%	<.01%	<.01%
2	2%-4%	.25% - .5%	.01%-.02%	.01%-.02%
3	4%-6%	.5% - .75%	.02%-.03%	.02%-.03%
4	6%-8%	.75%-1.0%	.03%-.04%	.03%-.04%
5	>8%	>1.0%	>.05%	>.05%

TABLE III. VALUES USE TO BIN FEATURE FOR LAST FOUR FEATURES

Bin Value	Feature type			
	Contours	***Forests North facing***	***Forests South facing***	***Vertical gain***
1	<1%	<5%	<5%	<-500'
2	1%-2%	5%-10%	5%-10%	-500' - 0
3	2%-3%	10%-15%	10%-15%	0-500'
4	3%-4%	15-25%	15-25%	500'-1000'
5	4%-5%	>25%	>25%	>1000'

E. Coding Target Values for Decision Trees

The subjective rankings are numerically encoded on a scale of 1 to 5, so they convert directly to decision tree target vectors.

F. Decision Tree Managment

The twenty route segments were randomly divided into training and testing sets. Twenty random combinations of training and testing sets were created for each experiment. The first experiment was performed with ten training sets and each of the resulting decision trees where tested on the ten unused data sets (testing sets). A second experiment was performed using fifteen randomly selected data sets for training and testing was performed on the five unused data sets.

Correct predictions by the decision tree were determined in two different ways. The first method accepted a decision tree prediction as correct only if the decision tree exactly predicted the subjective ranking. The second method accepted a decision tree prediction as correct if the decision tree predicted the subjective ranking plus or minus one ranking point.

G. Statistics

The split between training and testing sets was re-randomized for each of the twenty trials. Within each trial, the decision tree was trained on 10,000 iterations. For each of the twenty trials the number of correct predictions of the subjective rankings was collected on the test data. Mean and standard deviation for the 20 trials were calculated and confidence intervals were computed.

III. RESULTS

Fig. 9 to Fig. 12 show the experimental results for the two different training and testing set splits and for the two different methodologies (exact match and close match). Table IV shows the percent correct for each subjective category and for each experiment.

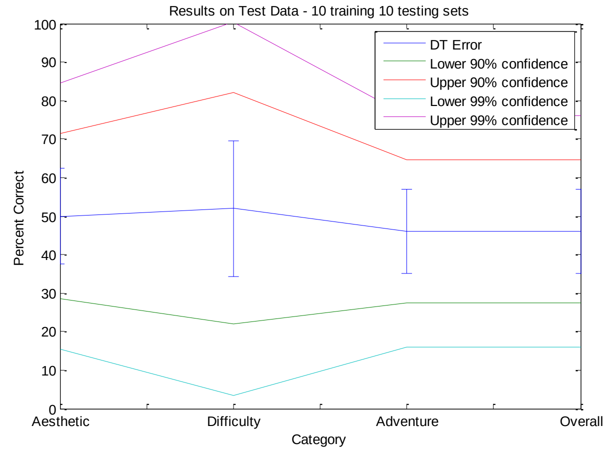

Fig. 9. Results with 10 Training Sets, 10 Testing Sets, Exact Match

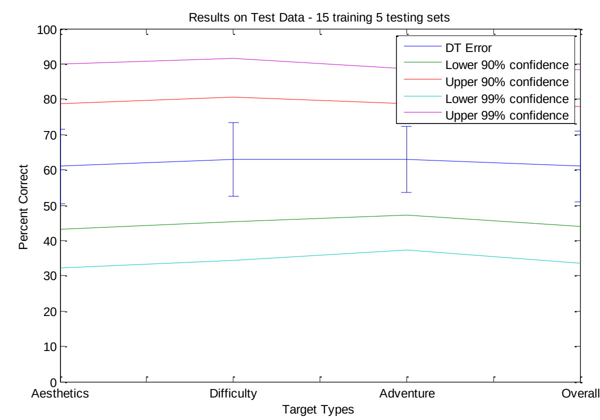

Fig. 10. Results with 15 Training, 5 Testing Sets, Exact Match

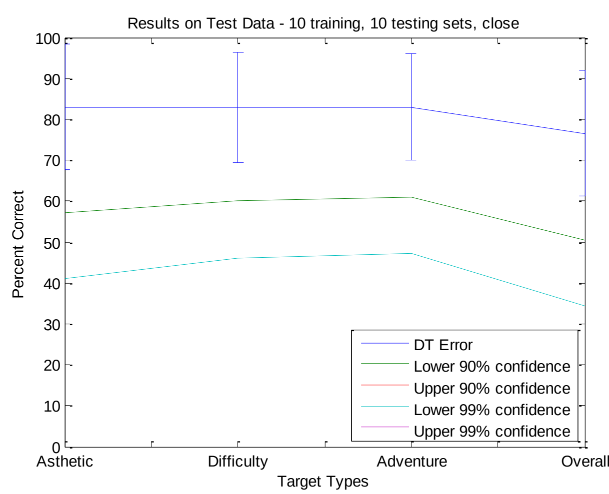

Fig. 11. Results with 10 Training sets, 10 Testing Sets, Approximate Match

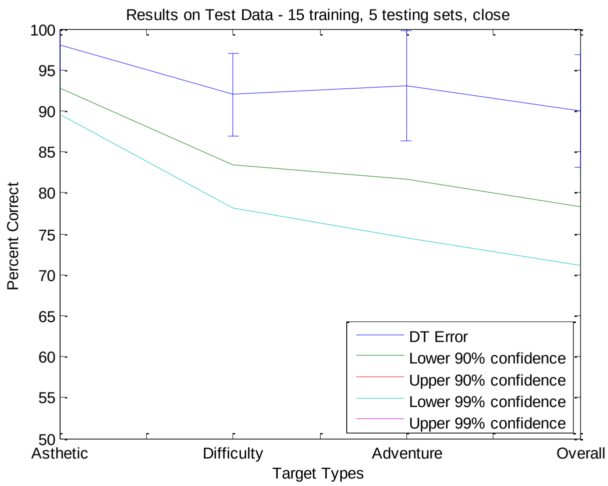

Fig. 12. Results with 15 Training sets, 5 Testing Sets, Approximate Match

For ten training sets, ten testing sets, and exact answers the decision tree predicts the subjective ranking correctly between 46% and 52% of the time. For fifteen training sets, five testing sets, and exact answers the predicted correct response increases to 61% to 63%.

However, for fifteen training sets and five testing sets, for each subjective ranking category, at least one of the combinations of training and testing sets produce a decision tree capable of predicting 100% of the subjective rankings correctly. This suggests that a wider range of training examples or more training examples could produce a decision tree that is better ability to predict subjective rankings.

If close answers are allowed, using ten training sets and ten testing sets the results range from 85% to 95% depending on the subjective ranking category. The results range from 90% to 98% accurate.

IV. Conclusions and Future Work

The results show that with ten training samples the DT was able to learn well enough to predict how the user would exactly rank routes based on topographic features 46% to 52% of the time. This compares well to the results of a random selection of one of the five ranking categories of 20%. Increasing the number of training samples to fifteen improved the decision trees ability to select exactly correct rankings to over 60%. Additionally, the results show that with the correct split of training and testing samples, the decision tree is able to predict 100% of the rankings correct.

The above two results suggest that increasing the number of training samples improves the accuracy of the prediction and that with enough training samples, this technique could be a good predictor of the exact subjective quality of a new route for a given subject.

TABLE IV. Percent Correct by Subjective Category

	Experiment (training sets/testing sets/method)			
	10/10/exact	***10/10/close***	***15/5/exact***	***15/5/close***
Aesthetic	50.0%	83.0%	61.0%	98.0%
Difficulty	52.0%	83.0%	62.0%	92.0%
Adventure	46.0%	83.0%	63.0%	92.0%
Overall	46.0%	76.5%	61.0%	90.0%

When close matches were allowed (predicted subjective ranking plus or minus one point from expected subjective ranking), the performance of the decision tree improved to 90% or greater with 15 training and 5 testing sets, with the aesthetic ranking being estimated 98% correctly.

While our research involved a single rider and a relatively small number of route segments, the results are promising. Additional areas for future research include:

- Involving a wider variety of subjects.
- Determining if the decision tree is better at predicting the subjective rankings of a new route for a subject that is an experienced topographic map reader vs. a subject that is an inexperienced at reading topographic maps
- Determining the relationship between the number of training routes and the accuracy at predicting the subjective ratings of new routes.
- Determining if the method transfers to other types of activities (e.g., skiing, hiking, or even wine tasting).

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