# 11B.4 DEVELOPMENT OF ALGORITHMS TO DETERMINE PRECIPITATION, PAVEMENT CONDITION, AND VISIBILITY HAZARDS ALONG ROADWAYS USING MOBILE OBSERVATIONS

Amanda R. S. Anderson*, Sheldon D. Drobot, Michael Chapman, Gerry Wiener, Brice Lambi
National Center for Atmospheric Research, Boulder, Colorado

Paul Pisano, Gabriel N. Guevara
Federal Highway Administration, Washington, District of Columbia

## 1. INTRODUCTION

This paper describes the current status of the roadway hazard algorithms in development at the National Center for Atmospheric Research (NCAR), including their development, as well as future work that is planned to further enhance them for real-time, operational use.

The algorithms will be included as part of NCAR's Vehicle Data Translator (VDT; Drobot et al. 2009). The VDT is a modular framework designed to ingest observations from vehicles, combine them with ancillary data such as radar reflectivity, flag the quality of the vehicle observations, and output the resulting data. Additional modules in the system compute statistics across road segments (e.g., mean temperature) and assessments of weather conditions on the corresponding road segment or grid point (e.g., slick pavement). These tasks are performed in the VDT in its three stages (Fig. 1). Stage 1 simply parses the mobile data and outputs it in a standard format for use in any end-user's applications. Stage 2 ingests the parsed data from Stage 1 along with ancillary data, such as radar reflectivity and surface station observations, and performs Quality Checking (QCh) on the mobile data. This QCh is similar to that of the *Clarus* system (Pisano et al. 2007). These data are outputted along road segments and in a gridded format, the sizes of which are user-determined. Stage 3 contains the inference module, where the QCh-ed mobile data and ancillary data are fed into algorithms to determine the precipitation, pavement condition, and visibility along the road segments. These algorithms are described in this paper.

**Corresponding author address:* Amanda R. S. Anderson, National Center for Atmospheric Research, P.O. Box 3000, Boulder, CO 80307;
email: aander@ucar.edu

## 2. DATA

The datasets used in the initial development of the algorithms were from the Detroit Test Environment (DTE; Andrews and Cops 2009) field experiments in 2009 (DTE09; Chapman et al. 2010) and 2010 (DTE10; Anderson et al. 2012) and the Data Use and Analysis Project (DUAP; Dion and Robinson 2009). All these datasets were collected in the Detroit, Michigan metro area. In the future, additional datasets from the Demonstration of CAN-bus Study (DOCS), which is being run along the Front Range of Colorado, the Minnesota Department of Transportation (DOT), and the Nevada DOT, will also be incorporated in the near future to further refine the algorithms.

Table 1 lists the observations currently used in the algorithms, both from the vehicles and from ancillary data. Speed ratio is the ratio between the vehicle speed and the speed limit on the road. The cloud mask is currently a binary cloud/no cloud field, but future plans include testing the more sophisticated Naval Research Laboratory (NRL) cloud classifier algorithm (Tag et al. 2000). Surface station observations are currently taken from the Automated Surface Observing System (ASOS) stations, but other stations such as those in the Road Weather Information System (RWIS; Manfredi et al. 2005) will be incorporated as well.

Table 1: Observations used in the hazard algorithms.

| Vehicles | Ancillary |
|---|---|
| Air Temperature | Radar Reflectivity |
| Wiper Status | Cloud Mask |
| Speed Ratio | Visibility (ASOS) |
| Headlight Status | Wind Speed (ASOS) |
| Anti-lock Brake System | Dewpoint (ASOS) |
| Traction/Stability Control | |
| Latitudinal/Longitudinal Acceleration | |
| Yaw Rate | |
| Steering Angle | |

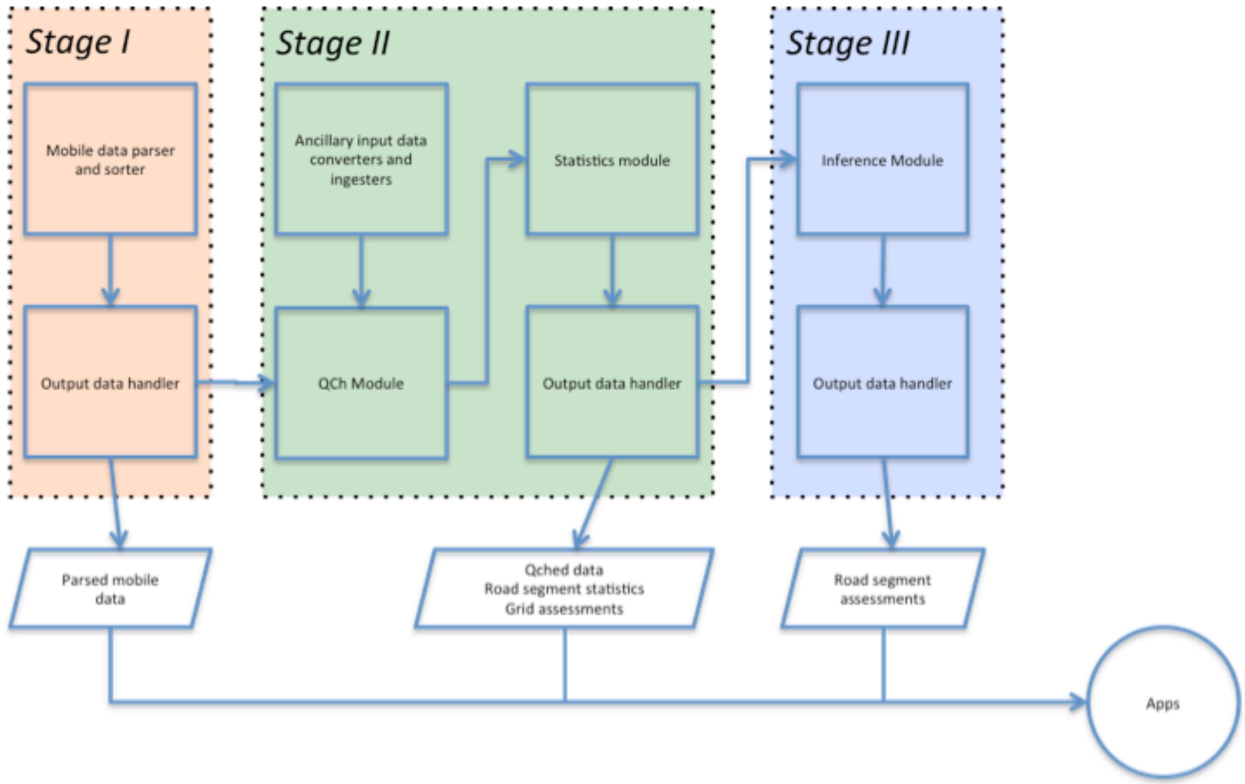


Fig. 1: Schematic of the VDT.

## 3. HAZARD ALGORITHMS

*a. Precipitation*

The precipitation algorithm's format is a decision tree with three branches based on air temperature: frozen-only output in cold temperatures, rain-only output in warm temperatures, and both outputs possible in temperature around 0°C (Fig. 2). The possible outputs for this algorithm are no precipitation, frozen, heavy frozen, rain, and heavy rain. It is planned to further categorize the possible frozen types (e.g., snow versus freezing rain), but there are not enough cases of non-snow frozen precipitation in the current datasets to allow such classifications at this point. The input data used in this algorithm is found in Table 2.

Preliminary testing of these algorithms was performed using driver reports from DTE10 as verification. The driver of each vehicle in the experiment was given a handheld voice recorder to use in recording conditions along the roadway as they encountered them. There are a few caveats to keep in mind with these reports. First, drivers were not given requirements for reporting, which led to non-continuous verification from each vehicle. For example, a driver might report that heavy snow is falling, but would not report when the heavy snow had stopped. Also, the driver reports were not always accurate in location and time, as it was up to the driver to report these. Finally, the reports were made subjectively, and they were not always consistent among drivers on the same route. For example, in one case, a driver reported a mix of rain and snow was falling, while the other two drivers reported only snow. Despite these caveats, the DTE10 driver reports have proven very useful in the initial development and testing of the algorithms.

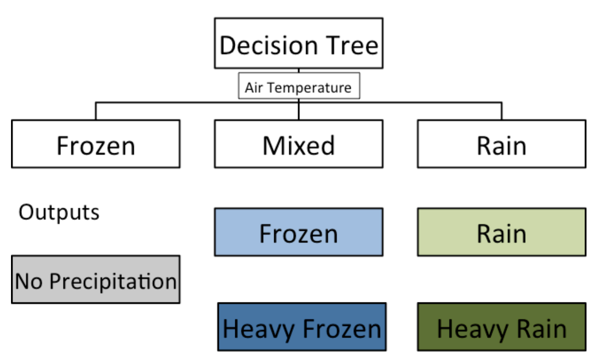


Fig. 2: Format of the precipitation algorithm.

Table 2: Input observations for the precipitation algorithm.

| Vehicle Data | Ancillary Data |
|---|---|
| Air Temperature | Radar Reflectivity |
| Wiper Status | Cloud Mask |
| Speed Ratio | Visibility (ASOS) |
| Headlight Status | |

When compared with DTE10 reports, only 11.1% of precipitation reports were misclassified by the algorithm. Most of the misclassifications were between light/moderate precipitation and heavy precipitation. Specifically reports of heavy precipitation were classified in the light/moderate category. When examining precipitation type misclassifications (frozen classified as rain or vice versa), most occurred in the mixed phase branch, indicating that the temperature criterion for the different branches was operating well.

*b. Pavement condition*

The pavement condition algorithm is in the format of “fuzzy sets”. For this format, each input observation has a corresponding interest function for each possible output. For each output, the interest values for each observation are added together, and the output with the highest interest is considered the most likely pavement condition for that segment.

A simple example of this format is given in Fig. 3. Here, there are two input observations: a speed ratio of 0.8 and a wiper status of 2 (intermittent). Each observation has a unique interest function depending on how likely certain values of that observation are to correspond with the given output, in this case the two possible outputs are slick or wet pavement. The value of the observation is plugged into each equation and these values added for each output. The slick output has an interest of 1 whereas the wet output has an interest of 2. In this example, wet pavement would be deemed more likely to be occurring along the road segment.

The possible outputs from the algorithm are dry, wet, road splash (where spray from surrounding vehicles causes a visibility hazard), snow, and slick pavement conditions. Input observations are given in Table 3.

Preliminary verification for this algorithm also used DTE10 driver reports. About 48.5% of the pavement conditions were misclassified. Dry pavement was classified the best. Snow-covered pavement and road splash were correctly classified about 50% of the time. The algorithm had a difficult time distinguishing between wet pavement and road splash, which is not surprising given that wet pavement often leads to road splash. The slick pavement part of the algorithm was also over-warning on slick conditions. More accurate pavement condition verification will be a valuable asset to improve these aspects of the algorithm.

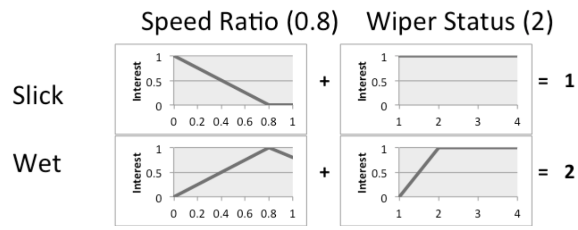


Fig. 3: Example of the format of the pavement condition algorithm.

Table 3: Input observations for the pavement condition algorithm.

| Vehicle Data | Ancillary Data |
|---|---|
| Speed Ratio | Radar Reflectivity |
| Air Temperature | |
| Wiper Status | |
| Traction/Stability Control | |
| Anti-lock Braking System | |
| Latitudinal/Longitudinal Acceleration | |
| Yaw Rate | |
| Steering Rate | |

*c. Visibility*

The visibility algorithm combines a decision tree and a system of fuzzy logic weights and functions. The decision tree portion of the algorithm uses output from the precipitation algorithm and other factors to determine if heavy rain or blowing snow is obscuring visibility. If not, the fuzzy logic portion of the algorithm is invoked to determine if the visibility has been compromised, regardless of the exact cause. An example of the fuzzy logic is given in Fig. 4. As with the pavement condition algorithm, each input observation has an interest, or likelihood, function associated with it. However, only one function is assigned to each observation. The outputs from these functions are each multiplied by different weights, with all the weights adding up to 1.0. The particular weight was derived from the importance of each observation in determining low vs. normal visibility. This was determined using regressions and automated data mining techniques. The interest values, after being multiplied by their associated weights, are added up for a final interest. Values above 0.5 are classified as low visibility, values below are classified as normal visibility. Input observations are given in Table 4.

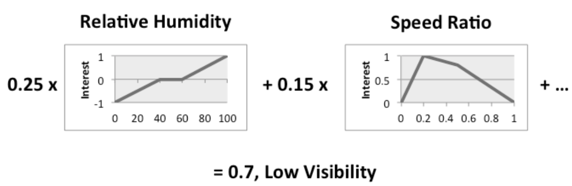


Fig. 4: Example of the fuzzy logic portion of the visibility algorithm.

Table 4: Input observations for the visibility algorithm.

| Vehicle Data | Ancillary Data |
|---|---|
| Wiper Status | Precipitation Algorithm Output |
| Air Temperature | Wind Speed (ASOS) |
| Relative Humidity (Dewpoint from ASOS) | Dewpoint (ASOS) |
| Headlight Status | Visibility (ASOS) |
| Speed Ratio | |

There were considerably fewer driver reports of visibility than for precipitation and pavement condition. Therefore, the algorithm was first tested with the nearest ASOS station visibility. It is important to keep in mind that this is not the most reliable verification due to the ASOS visibility being an input into the fuzzy logic (weight of 0.1). In addition to being input, the ASOS was approximately 45 km from the testbed, so local variations could result in differing conditions in the two locations. However, it did offer some insight into how the algorithm was performing. When testing the fuzzy logic portion, 20.7% of normal and low visibility observations were misclassified. Focusing on only low visibility, the Critical Success Index (CSI) was found to be 0.27. Calculating the CSI for the few driver reports of low visibility yielded a much higher CSI of 0.59.

## 4. FUTURE DIRECTIONS

As development on the algorithms continues, use will be made of the DOCS, Minnesota DOT, and Nevada DOT data to further tune and verify the algorithms. The DOCS data will be particularly useful as a video camera is being used to collect verification images of every segment of roadway travelled. The state DOT data will be a good for testing data from real-time operations.

The DOCS work will also allow for controlled testing to target areas of verification that are lacking, such as mixed precipitation and accurate pavement conditions. As more data are accumulated, automated data mining techniques will provide another method of continued development. A major emphasis of the algorithm development will involve increasing verification efforts to improve tuning.

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