



# The Safety Effect of the Red Light Running Cameras: Applying Data Mining Techniques Using Fatality Analysis Reporting System (FARS) Data

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## 1. INTRODUCTION

Initially, our paper reviews prior literature and techniques on the effectiveness of red-light cameras in terms of traffic accidents, injuries, fatalities, red-light tickets, and cost. We then apply data mining techniques to examine the data stored in the U.S. Department of Transportation's key database on vehicle fatalities to try to tease patterns and rules related to red-light controlled intersections.

## 2. LITERATURE REVIEW

From 1992 to 2000, the number of fatal crashes at signal-controlled intersections in the United States increased by 19 percent (IIHS, 2001). Red light running (RLR) was the single most frequent cause of these crashes, as pointed out by the Insurance Institute for Highway Safety (IIHS, 2001) and equivalent to more than three times the rate of increase for all other fatal crashes during the same period. According to the Federal Highway Administration (FHWA), crash statistics show that nearly 1,000 Americans were killed and 176,000 were injured in 2003 due to RLR related crashes. The monetary impact of crashes to the society is approximately \$14 billion annually (FHWA, 2005). The California Highway Patrol estimates that each RLR fatality costs the United States \$2,600,000 and other RLR crashes cost between \$2,000 and \$183,000, depending on severity (CA Bureau of State Audits, 2002).

A 2005 study conducted within the District of Columbia by Wilber and Willis (2005) showed remarkably different results than most of the other studies:

*"The analysis shows that the number of crashes at locations with cameras more than doubled, from 365 collisions in 1998 to 755 last year. Injury and fatal crashes climbed 81 percent, from 144 such wrecks to 262. Broadside crashes, also known as right angle or T-bone collisions, rose 30 percent, from 81 to 106 during that time frame. Traffic specialists say broadside collisions are especially dangerous because the sides are the most vulnerable areas of cars" (Wilber & Willis, 2005).*

The study argues that crashes and injuries may have *increased* despite or because of the red light cameras. Some of this increase may be related

to increased traffic rates. "The study found that rear-end crashes rose 15 percent at camera locations. But because broadside crashes are more dangerous and cause greater damage, the study concluded that the cameras can help reduce the costs of traffic accidents" (Wilber & Willis, 2005).

But there are some limitations in the study. First, it doesn't account for spillover effects, where the benefits of cameras at some locations can be reflected at sites without cameras. Second, the study blames the city for focusing solely on revenues, even though the city was acting in the interest of public safety because data showed initial improvements, prior to the long-term study presented by The Washington Post and the city had not expanded the program significantly prior to the results of a long-term study (Wilber & Willis, 2005).

## 3. DATA MINING

In response to the controversy of whether it's ultimately a safety tool to reduce red light running and traffic crashes, our research applies data mining techniques to traffic data collected in Washington D.C. and Maryland to determine the supporting data patterns. Traffic data has been collected from the U.S. Department of Transportation's Fatality Analysis Reporting System (FARS) database (see Table 1).

Based on our analysis, data mining techniques have not been used in the past to evaluate the effectiveness of red light camera enforcement. Our study applies data mining techniques to contribute to past research.

For our research, we narrowed the data to the years 2000-2003 and for only Maryland and Washington DC. First, we limited data to all fatal crashes where a violation for red-light running was charged. Second, we limited the original data to fatal crashes at signal-controlled intersections, whether a ticket was issued or not. We used C5.0, C&RT and CHAID decision tree models, as well as K-Means and Neural Network models for the data mining analysis.

As indicated by the results of K-Means Models, car collisions are more likely to happen on Fridays and Sundays. Types of car crashes involved in running red lights are mostly rear-end crashes and angle front-to-side collisions, as 1,517 cases and 890 cases were recorded, respectively. On the other hand, results of Neural Network Models show the relationships between fatal crashes at red-light-signal controlled intersections and harmful events, and between fatal crashes at red-light-signal controlled intersections and the manner of collision. The strongest relationship is a collision with another moving object, most likely another vehicle. The second strongest link is between fatal crashes and pedestrians. With the respect to the nature of the crash, the strongest relationships are angle and front-to-side collisions.

Table 1. FARS Major Variables Used in Our Data Mining Application

Variable	Description	Examples Used
<b>VIOLCHG1</b> or <b>VIOLCHG2</b> or <b>VIOLCHG3</b>	Violations Charged (99 factors)	1 Fail to Stop for Red Signal 2 Fail to Stop for Flashing Red 3 Violation of Turn on Red 4 Fail to Obey Flashing Signal (Yellow or Red) 5 Fail to Obey Signal Generally 6 Other
<b>DAY_WEEK</b>	Date of the crash/accident	1 Sunday 2 Monday 3 Tuesday 4 Wednesday 5 Thursday 6 Friday 7 Saturday 8 Unknown
<b>HARM_EV</b>  <b>M_HARM</b>	First harmful event applies to the crash. (50 events)  The most harmful event variable applies to the vehicle (50 event)	1 Traffic Signal Support 2 Fell from Vehicle 3 Thrown or Falling Object 4 Culvert 5 Curb 6 Unknown
<b>MAN_COLL</b>	Manner of Collision	0 Not Collision with Motor Vehicle in Transport 1 Front-to-Rear (Includes Rear-End) 2 Front-to-Front (Includes Head-On) 3 Angle - Front-to-Side, Same Direction 4 Angle - Front-to-Side, Opposite Direction 5 Angle - Front-to-Side, Right Angle 6 Angle - Front-to-Side/Angle-Direction Not Specified 7 Sideswipe - Same Direction 8 Sideswipe - Opposite Direction 9 Rear-to-Side 10 Rear-to-Rear 11 Other (End-Swipes and Others) 99 Unknown

For future work, our data was not specific to intersections and further research is being conducted to examine violations before the camera is installed, a short time lag after the camera is installed (6 months – 2 years), and after a significant time period has passed after the camera is installed (5 – 10 years).

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