Data Fusion to Improve the Accuracy of Traffic Counts

Final Report

by

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DISCLAIMER

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16. Abstract

This study investigated the use of data fusion of two different traffic counting and classification methods. While sensor level fusion using thermal and optical images was investigated, it was not found useful by our approaches. The decision-level fusion method for pneumatic tube and infrared video is presented. The method was validated at three different locations in South Carolina. Errors in vehicle counts and vehicle classification were calculated using manual data collection from recorded videos as the baseline. In all locations, the results of data fusion are more accurate in both vehicle counts and vehicle classification when compared to either of the methods alone.

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EXECUTIVE SUMMARY

This project presents a study of integrating more than one method of collecting traffic counts by vehicle classification. Specifically, the use of infrared and optical imaging as well as the use of a pneumatic tube and infrared video were explored. The integration of multiple sensor data is known as data fusion. Data fusion can be implemented at the local (pixel) level, an intermediate level (feature level), or as a final processing step after each sensor data has been individually processed (decision level). The results from a pixel-level fusion of infrared and optical images were not successful in our attempts. The fusion of pneumatic tube and infrared video is implemented using a four-rule decision tree. The error in vehicle counts and vehicle class were calculated from manually classified data using a video recording at each test site. The use of a recording is known to limit the errors in manually classified data when compared to the use of real-time collection which may limit one's ability to review the results. The fused data is found to reduce both counting and classification errors when compared to either method alone.

Data from three validation studies at various locations in South Carolina are presented. Errors in both counts (non-existing vehicles or missing counts) as well as correctly counting but misclassified vehicles are given for each measurement method alone and for the data fusion results. At the first location (Rosewood drive) 81 vehicles passed through the measured lane. During the duration of the analyzed data, the pneumatic tube miss counted four vehicles and misclassified one. The infrared system miss counted 15 vehicles and misclassified one. The combined system miscounted two vehicles and misclassified none. At this location, data fusion reduced the counting errors by 50% compared to the best values from the best data resulting from a single method.

At the second validation location (Old Dunbar Road) with 226 vehicles during the study period, the fused data reduced the errors (both classification and counting) to zero while each method alone had errors. At the third validation location (Pineview Road) with 172 vehicles during the study period, the pneumatic tube measurements had eight miscounts and four miss classified errors. The infrared video measurements had 11 miscounts and four misclassified while the fused data resulted in no miscounts and two misclassified.

From the validation results, the source of errors in the two systems appears to arise from different mechanisms and can be compensatory. The data fusion results always resulted in smaller errors in both classification and count. Where the need for accurate counts outweighs any additional cost associated with multiple measurement methods, the use of data fusion is indicated.

CHAPTER 1

Introduction

1.1 Motivation

Accurate counts of current modes of transport are required for the optimal allocation of resources for both maintenance and upgrades of the transportation system. Current traffic counting systems often only measure one transportation mode accurately and extrapolate to other modes. Reduction in the cost of hardware and increases in computer performances makes the use of multiple sensing methods feasible. As the cost of hardware decreases, multiple data collection systems can be used at the same location. There is a plethora of methods to measure traffic (tube, light, infrared, radar, video, and cell phone signals). However, each measurement techniques have a different distribution of errors in each vehicle type classification.

It is hypothesized that the use of different traffic sensing methods and using data fusion will compensate for different measurement errors and provide a more accurate vehicle count and vehicle classification. This approach allows us to improve the fidelity of the data collected on the traffic modes analyzed.

1.2 Methodology

The primary objective of this research was to develop algorithms for enhancing vehicle counting based on a single measurement technique by combining data from multiple sensing methods. Specifically, pneumatic tube data and infrared camera-based methods were used. These two vehicles counting approaches rely on distinct sensing methods, independent data reduction and calibration. The existing independent data processing for each method was not changed in this project. Counts by vehicle type were collected by both methods and fused using the developed algorithm into a more accurate vehicle count by vehicle type.

The methodology followed for the construction of the data fusion algorithm was:

1. **Review existing performance:** We examined several sets of Pneumatic tube data with RGB video recordings to evaluate the types of count/classification errors that occurred.
2. **Test data collection:** We use infrared video recordings and pneumatic tube data collected simultaneously at three different locations in South Carolina during different weather conditions.
3. **Data processing:** The raw data were independently processed to construct vehicle time-type pairs. The pneumatic tube data were analyzed using software from MetroCount (2013). The infrared videos were analyzed using the program DECAF (Huynh et al., 2021) developed by the research team under contract with SCDOT. In addition, the videos were manually classified by the research team and this manual classification provides the ground truth. One should note that the

manual classification was done using video recordings of each vehicle crossing. This ground truth method is significantly different than real-time manual counting which is known to have significant errors as images can be reviewed as needed until classification is almost certain.

4. **Performance of data fusion:** Finally, we measured the improvement in the accuracy of the vehicle counts using the fused data. This measurement used data not incorporated into the fusion algorithm development.

CHAPTER 2

Literature Review

The literature review in this report covers some of the backgrounds on the reported accuracy of pneumatic tube measurements, infrared video-based classification, and data fusion methods.

2.1 Pneumatic tubes

Pneumatic tubes have been used in traffic counting for years. By the 1930's several patents on pneumatic tube devices for detecting and counting vehicles exist (Salsbury 1931, Stubbins 1936). The method is based on recording the pressure generated when a tire crosses an elastomeric hose. Pneumatic tubes count axial tube interactions which have to be converted into vehicle number and type. Vehicle direction and speed can be determined using two parallel sensors placed perpendicular to the traffic flow at a fixed offset distance. Timing data can identify both speed and axial spacing. Vehicle counts are determined by classifying multi-vehicle headway events from intra-vehicle spacing (Avery et al. 2004). Finally, vehicle classification is determined from axial spacing and headway. (Metrocount, 2013).

The accuracy of pneumatic tube counts and classifications was studied by several researchers.

Davies and Salter (1983) reported errors in classification using combined triboelectric axel counting (similar to pneumatic tube data) with induction loops. They compared errors using a baseline determined from film data that was manually extracted. Three locations were recorded and up to 7823 images were used to verify the data and the most traveled site. They report classification data errors that in one case exceeded 200% with typical values between 50% and 0%.

Mendigorin, Peachman, and White (2003) compare pneumatic tube counts and classifications with manually collected data retrieved from video records. The data collected was from six locations and two-hour video recordings from each site was used to validate the data. They found that pneumatic tubes performed well with an error in counts of less than 4% in all sites studied. At most of the locations, the count error was around 0.5% The classification errors are larger. The worst-case error in classification was over 50%

McGowen and Sanderson (2011) measured vehicle count using pneumatic tube data at several locations on a roadway with no access points between measurement locations. They also compared pneumatic tube results with real-time human counts. The study was conducted at four locations with three of the locations using comparison with real-time manual counts. The duration of the manual counts were two and a quarter hours, one hour and two hours. They found that the error in vehicle counts was less than 4% when compared to real-time manual counts.

2.2 Video object detection

An extensive literature review of video-based traffic counting and classification is given in an earlier C2M2 report (Huynh 2019) as well as in the papers by Boukerche, et al. (2017). It was reported that among the object recognition methods, Convolutional Neural Networks (CNNs) are the most widely used for newer video traffic counting and classifications. There are two different approaches to applying CNNs: supervised and unsupervised. Supervised learning is an approach that is defined by its use of labeled datasets. That is, the datasets are designed to train or "supervise" algorithms into classifying data or predicting outcomes accurately. On the other hand, unsupervised algorithms discover hidden patterns in data without the need for human intervention (Delua, 2021). The supervised CNN approach is the more popular of the two and it is the one that is utilized in the measurements employed in this project. A new video-based classification system using infrared images was used in this project. (Huynh et al. 2021).

Infrared images were found to be more robust at night as well as less dependent on weather when compared to an optical video. The infrared video system will be referred to by the software name DECAF in the rest of this report.

2.3 Data fusion

Data fusion is the process of fusing multiple data sources or methods to produce a better outcome than that provided by any individual data source or method. Data fusion provides several advantages over a single sensor by improving precision, and availability, and reducing uncertainty in data. It is a formal outline used to prompt the inclusion of data from different sources. Data is a measurement of the environment that is generated by a sensor. Feature extraction, determined by an analysis of the data, is a variable that can be used in a class approach. Data fusion can be categorized into three main class levels: pixel-level fusion, feature-level fusion, and decision-level fusion. In this thesis, we are attempting to find the more efficient level of fusion to fuse DECAF data et MetroCount data.

2.3.1 Pixel-level fusion

Several methods for fusing data from different spectrum data or multiple images exist in the literature.

Zhang and Blum (1999) proposed a new low-level fusion technique, named discrete wavelet frame (DWF). They evaluated the effectiveness of their proposed method against previously developed techniques: Laplacian pyramid transform (LPT), Daubechies's D8 orthonormal (DWT), and discrete wavelet transform (DWT). This was accomplished using images of the same scene. Their experiment results indicated that DWF outperformed all the other techniques by more than 2.4%.

Kumar and Dass (2009) proposed a total variation (TV) based approach as a new low-level fusion method to fuse images acquired using multiple sensors. They evaluated the effectiveness of their proposed method against the least squares estimate (LSE) method. The proposed fusion approach was applied to medical and aircraft navigation image data sets. Their experiment results indicated that TV outperformed the LSE method by 8% on average for the medical image dataset and by 7 % on average for the aircraft navigation image dataset.

Lallier and Farooq (2000) proposed a new low-level fusion technique named the pixel-level weighted average (PLWA). They evaluated the effectiveness of their proposed method against other fusion methods such as the image level weighted average (ILWA), the difference of low-pass (DoLP), the ratio of low-pass (RoLP), Gradient, Wavelets, and Toet's False Color. This experiment was accomplished through the fusion of visual and thermal images. It was demonstrated that on average, the images produced by the PLWA method were of quality equal to or superior to those produced by the other image fusion methods in the literature.

2.3.2 Feature-level fusion

Feature-based fusion is most often done with similar data types such as infrared and video images or images and synthetic aperture radar (SAR). Such measurements have similar feature taxonomy.

Lan, Ma et al. (2015) proposed a new feature-level fusion named robust joint sparse representation-based feature-level fusion tracker (RJSRFFT). They evaluated the effectiveness of their proposed method against both sparse representation-based and fusion-based-trackers. This was accomplished using both synthetic data and real videos from publicly available datasets. Their experiment results indicate that RJSRFFT outperforms other feature fusion-based trackers and sparse representation-based trackers under appearance variations such as occlusion, scale, illumination, and poses which can be shown in the experimental results.

Reiche, Souza et al. (2013) proposed a new approach for feature fusion of multi-temporal and medium-resolution SAR and optical subpixel fraction information. They evaluated the effectiveness of their proposed method compared with potential Landsat-only or PALSAR-only approaches for a heavy cloud-contaminated tropical environment. After independently processing SAR and optical input data streams the extracted SAR and optical subpixel fraction features are fused using a decision tree classifier. This was accomplished by mapping tropical FLC and detecting deforestation and forest degradation. The overall accuracies are on average 5.1% and 5.7% better for mapping forest land cover deforestation and degradation, respectively compared with potential Landsat-only or PALSAR-only approaches.

Kong, Zhang et al. (2006) proposed a feature-level fusion approach for improving the efficiency of palmprint identification. They employed Multiple elliptical Gabor filters with different orientations to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the Fusion Code. They evaluated the effectiveness of their proposed method compared with the previous non-fusion approach. With a testing database containing 9599 palmprint images from 488 different palms, the proposed method achieves around 15% verification improvement compared to the previous non-fusion approach.

2.3.3 Decision-level fusion

Decision-level fusion can treat each measurement method as a stand-alone system and only integrates the information from each system using independently processed data.

Kalluri, Prasad et al. (2010) proposed a new approach for the decision-level fusion of the spectral reflectance information with the spectral derivative information for robust land cover classification. This paper differs from previous work because they proposed effective classification strategies to alleviate the increased over-dimensionality problem introduced by the addition of the spectral derivatives for hyperspectral classification. They evaluated the effectiveness of their proposed method against a decision-level fusion without the addition of the spectral derivatives. This experiment was accomplished with handheld, airborne, and spaceborne hyperspectral data. The overall accuracies are on average 4.7 % better with the addition of the spectral derivatives.

Prabhakar and Jain (2002) proposed a new method for classifier combination at a decision level which stresses the importance of classifier selection during combination. The proposed combination scheme either outperforms or matches the performance of the sum rule and outperforms the product rule in all the two- three- and four-matcher combinations. This experiment was conducted on a large fingerprint database, (~2700 fingerprints). The overall matching performance is around 3% better than the proposed combination.

Li, Qiu et al. (2018) proposed a new method named C2D-CNN (color 2-dimensional principal component analysis (2DPCA)-convolutional neural network). C2D-CNN combines the features learned from the original pixels with the image representation learned by CNN and then makes decision-level fusion, which significantly improves the performance of face recognition. They evaluated the effectiveness of their proposed method against other CNN: CNN-0, CNN-1, and CNN-2. Their experimental results indicated that C2D-CNN outperformed all the other CNN by more than 10%.

CHAPTER 3

Methods

As stated in the literature review, data fusion can be categorized into three types: pixel-level fusion, feature-level fusion, and decision-level fusion. The methods used in this research are organized using the same three types of fusion. The procedures that are used are focused on finding a method to combine DECAF data with MetroCount data.

3.1 Data collection

3.1.1 Pneumatic tube

The pneumatic tube data was collected with the cooperation of the SCDOT using equipment from MetroCount. Two tubes of equal length must be placed parallel to each other and spaced 3 feet apart. The tubes must be nailed on each end of the roads and taped down every 3 feet, to prevent any movement from the tubes. The pneumatics tubes must be placed on roads with constant speed across the tubes and away from intersections. Figure 1 shows a typical installation.

Figure 1: Pneumatic tubes deployed on Walter Price Road, Columbia, SC

Once the data is collected using the pneumatics tubes, MetroCount software uses the time between each axle of the vehicles going over the tubes to detect and classify each vehicle passing over the pneumatic tubes. The software ("MetroCount Traffic Executive") was used without any recalibration from the SCDOT standard practice. The results of the pneumatic tube data were downloaded from the device as a CSV file with time-stamp and vehicle classification. All 13 vehicle classes defined by the FHWA are used (See Figure 2).

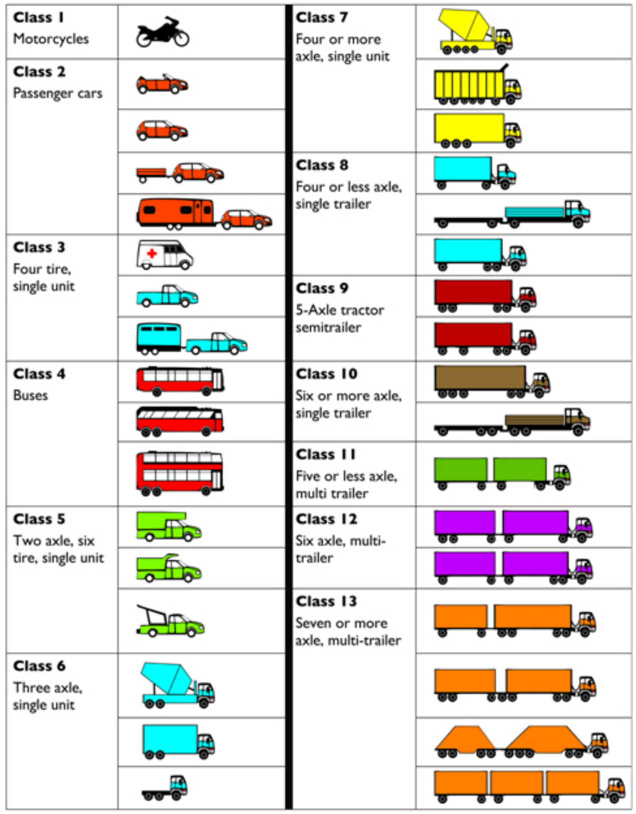

Figure 2: FHWA's 13 vehicle category classification (from FHWA website)

3.1.2 DECAF

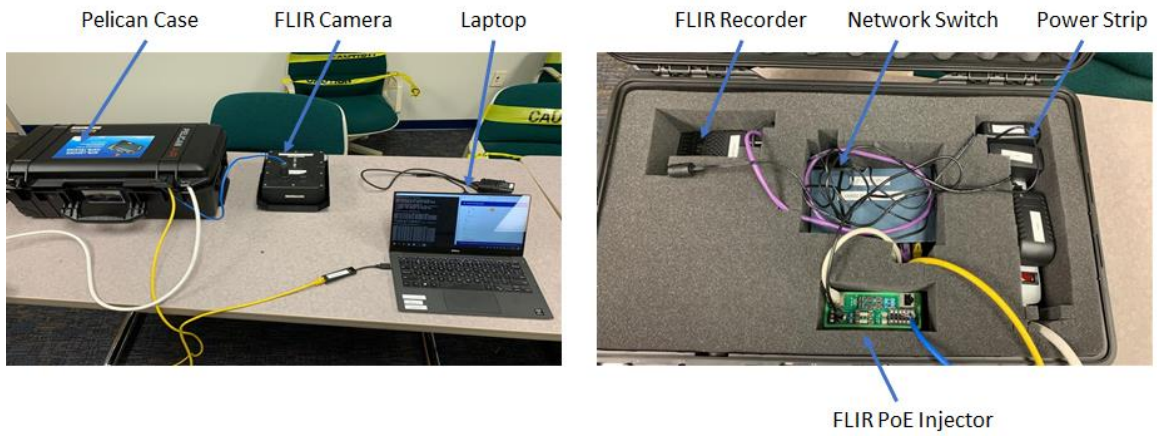

Figure 3: FLIR Sense2 Dual camera components and assembly

A TraficSense2 Dual camera was procured from FLIR to collect the IR videos. The camera system is shown in **Error! Reference source not found.Error! Reference source not found.**, the thermal camera is connected to a PoE (Power over Ethernet) module. It is also connected to a Raspberry Pi via a network switch; the Raspberry Pi runs a recorder software that stores the video data onto an external hard drive.

Figure 4 shows how the thermal camera was mounted onto the trailer during one of the field deployments. The thermal videos were collected with a 640 by 480 pixels resolution and a frame rate is 30 frames per second.

Figure 4: Thermal camera and trailer at a data collection site

The DECAF software provides grouped vehicle classification following the FHWA definitions of vehicle types. The four groupings provide by DECAF are:

Group 1 Class 1
Group 2 Class 2-3
Group 3 Class 4-5
Group 4 Class 6-13

The DECAF software not recalibrated for this study.

3.2 Pixel-level fusion

While not based on only infrared and Metrocount data, we did explore the use of one low-level method using both infrared (IR) and conventional Red-Green-Blue (RGB) video data. The images are matched to correct for the offset in sensor location as well as sensor resolution. The fusion procedure was to transform the RGB data into Hue, Saturation, and Luminosity (HSL). The IR data will be used to modify the luminosity at each pixel value. Several functions were explored to modify the luminosity including replacing luminosity with the max of Intensity and IR data or using some additive function such as Intensity/2+IR/2. The modified HSL data is then transformed back to RGB format.

The CNN is then trained again starting with the existing weights and using the additional modified RGB images to improve the performance using this fused data.

3.3 Feature-level fusion

In this project, one of the two sources of data was from pneumatic tubes. Using the Metrocount data, very limited access to feature-level data was available. Thus, the decision was made not to explore future feature-level data in this project.

3.4 Decision-level fusion

Decision-level fusion takes symbolic representations as sources and combines them to obtain a more accurate decision. With this level, each level has made a preliminary determination of an entity's location, attributes, and identity before combining everything. Decision-level algorithms are used as weighted decision, Bayesian inference, and Dempster-Shafer's method. One technique of decision fusion (high-level fusion) is detection probability. Using detection probability, the relation of a point by a single sensor to the distance between them can be derived into a value.

A high-level method could be utilized by fusing two different data sources. The vehicle detection and classification results from DECAF and MetroCount are to be combined. Then using a decision tree, voting will be done resulting in the fused data.

With the data available, a decision-level fusion using MetroCount, and DECAF is the more feasible fusion that can be done. The developed decision rules to fuse the DECAF and MetroCount results are based on several observations about their respective performance as illustrated in Figure 5. MetroCount detects vehicles when the tubes are compressed which will only occur if an actual vehicle traveled over them, whereas DECAF could have false detection due to camera motion. For this reason, MetroCount is considered to have higher fidelity than DECAF for vehicle detection. Due to the difference in the start and endpoint of their detection zones, the time in which vehicles are detected by the respective methods differs by about two seconds. The time varies on the speed and size of the vehicle.

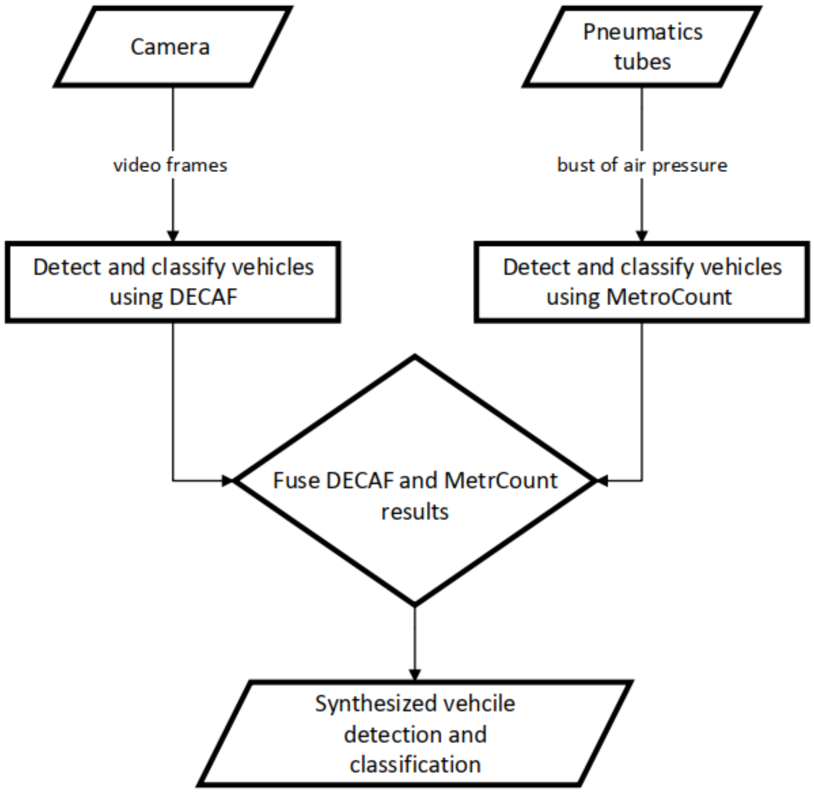

Figure 5: Decision-level fusion diagram

MetroCount and DECAF produce a vehicle-by-vehicle CSV report that includes the time the vehicle was detected and its type. The initial temporal offset in the measurements was computed using best-fit optimization to match only the vehicle count and not the vehicle type. A fixed temporal offset was used. The following decision rules were used to fuse the data:

1. If a vehicle is detected and classified by DECAF and is within two seconds of MetroCount, then an actual vehicle must have traversed the detection area. The pneumatic tube records the presence of a vehicle at the tube location, while the video method identifies the presence of a vehicle within a region of interest. Due to the need of having the camera pointed in the direction of traffic, the camera had to be deployed upstream of the pneumatic tubes. The different measurement locations resulted in data being time-stamped at a difference instant. Depending on the speed of each vehicle there can be a time discrepancy of up to two seconds. This vehicle should be included in the synthesized output. In addition, this vehicle should be assigned the group of the method with the highest classification rate.

2. If a vehicle is detected by DECAF but not MetroCount, then there is a high probability that it was a false detection. This vehicle will not be included in the synthesized output.

3. If a vehicle is detected by MetroCount but not DECAF, this vehicle should be included in the synthesized output.

4. If a class 4 vehicle is detected by DECAF and multiple group 2 vehicles are detected by MetroCount, then a single group 4 vehicle should be included in the synthesized output.

CHAPTER 4

Results

4.1 Pixel-level data fusion

In our hands, we found that all methods to apply pixel-level fusion failed to improve classification accuracy. Using the equipment available to the researchers, the parallax errors and interpolating values over different image resolutions resulted in a fused image that had lower classification accuracy than the IR or RGB images had alone. Because of these difficulties, the project concentrated on developing a feature-level fusion method.

4.2 Feature-level data fusion

The decision rules proposed in section 3.3 were used to study the fusion of three different data sets collected on three days. The locations were on Rosewood Drive (collected on March 24, 2021 starting at 11am.), Old Dunbar Road (collected on March 4, 2021), and Pineview Road (collected February 17, 2021) in Richland County, SC. Two hours of data were analyzed at each location.

The results are summarized for Rosewood Drive in Table 1. In this table, the number of errors for the MetroCount, DECAF, and the errors after using the data fusion algorithm is presented. The ground truth, extracted by manual observation of the video data, is also given. Vehicles that are not detected or vehicles that were detected multiple times were identified as miscounted (Count). Vehicles that were detected but had the wrong classification were identified as misclassified vehicles (Class).

Table 1: Comparison of DECAF, MetroCount, and Data Fusion methods for Rosewood Drive Traffic Counts

Classes	**MetroCount**	**DECAF**	**Data Fusion**	**Actual Count**
	Count/Class	Count/Class	Count/Class	
Class 1	1/0	0/0	0/0	0
Class 2-3	3/0	4/0	2/0	40
Class 4-5	0/0	0/1	0/0	2
Class 6-13	0/1	11/0	0/0	39
Total	4/1	15/1	2/0	81

At this location, the traffic was more than half composed of trucks. MetroCount miscounted 4 vehicles on an actual count of 81 vehicles, an error rate of 5%. In terms of classification, MetroCount misclassified 1 vehicle, with an error rate of 1%. DECAF miscounted 15 vehicles on an actual count of 81 vehicles, an error rate of 18%. DECAF misclassified 1 vehicle, with an error rate of 1%. After data fusion, the results miscounted 2 vehicles for an error of 2%, and it misclassified 0 vehicles. Therefore, for the Rosewood Drive traffic counts, using the proposed Data Fusion method yields an 88% relative improvement in classification errors compared to using DECAF alone and a 50% relative improvement over MetroCount alone.

Table 2: Comparison of DECAF, MetroCount, and data fusion on Old Dunbar Road

Classes	**MetroCount**	**DECAF**	**data fusion**	**Actual Count**
	Count/Class	Count/Class	Count/Class	
Class 1	0/0	2/0	0/0	2
Class 2-3	1/0	29/3	0/0	206
Class 4-5	0/0	0/6	0/0	6
Class 6-13	0/1	0/4	0/0	12
Total	0/1	31/13	0/0	226

The Old Dunbar test results shown in Table 2 indicate that MetroCount did not miscount any vehicles. In terms of classification, MetroCount misclassified 1 vehicle on an actual count of 226 vehicles, an error of 0.01%. DECAF miscounted 31 vehicles on an actual count of 226 vehicles, an error rate of 14%. DECAF misclassified 13 vehicles, an error of 5%. The data fusion method did not miscount nor misclassified any vehicles. Therefore, for the Old Dunbar traffic counts, using the proposed Data Fusion method yields a 100% relative improvement of DECAF and did not significantly improve MetroCount accuracy. One should note that the actual traffic count is primarily from cars (Class 2-3) and one would expect low misclassifications from MetroCount.

Table 3: Comparison of DECAF, MetroCount, and data fusion on Pineview Road.

Classes	**MetroCount**	**DECAF**	**data fusion**	**Actual Count**
	Count/Class	Count/Class	Count/Class	
Class 1	1/0	0/0	0/0	0
Class 2-3	7/0	11/2	0/1	155
Class 4-5	0/0	0/2	0/1	2
Class 6-13	0/4	0/0	0/0	15
Total	8/4	11/4	0/2	172

The Pineview Road test results are shown in Table 3. The actual traffic is again composed of 90% cars (Class 2-3). The results indicate that MetroCount miscounted 8 vehicles on an actual count of 172 vehicles, an error of 5%. In terms of classification, MetroCount misclassified 4 vehicles, an error of 2%. DECAF miscounted 11 vehicles on an actual count of 172 vehicles, an error rate of 18%. DECAF misclassified 4 vehicles, an error of 2%. The data fusion method did not miscount any vehicle and it misclassified 2 vehicles, an error of 1%. Therefore, for the Pineview Road traffic counts, using the proposed Data Fusion method yields a 100 % relative improvement over DECAF and a 100% relative improvement over MetroCount.

CHAPTER 5

Conclusions

The accuracy of an infrared video traffic counting system (DECAF) and a pneumatic tube system (MetroCount) were measured based on a ground truth determined by human counting from the video. As it was done offline, the ground truth data is not subject to counting/classification errors when done by real-time human measurement. Both systems had counting errors as well as errors in vehicle classification. However, both measurements were within commonly acceptable values, with MetroCount having an overall smaller error rate.

Data fusion using RGB video and IR video did not prove to be useful at the pixel level. A set of four decision rules were constructed to perform data fusion at the decision level. Using these rules in a fusion algorithm, the corresponding fusion of DECAF and MetroCount and DECAF data resulted in a reduction in both count and classification errors in most of the measured data. The fusion data did not increase the errors in any case studied. Thus, the combination of IR video and pneumatic tube data can provide more accurate traffic counts as well as more accurate classification of vehicle types compared to using only one method for traffic counting.

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