MULTI-MODAL SENSOR REGISTRATION FOR VEHICLE PERCEPTION VIA DEEP NEURAL NETWORKS

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ABSTRACT

The ability to simultaneously leverage multiple modes of sensor information is critical for perception of an automated vehicle's physical surroundings. Spatio-temporal alignment of registration of the incoming information is often a prerequisite to analyzing the fused data. The persistence and reliability of multi-modal registration is therefore the key to the stability of decision support systems ingesting the fused information. LiDAR-video systems like on those many driverless cars are a common example of where keeping the LiDAR and video channels registered to common physical features is important. We develop a deep learning method that takes multiple channels of heterogeneous data, to detect the misalignment of the LiDAR-video inputs. A number of variations were tested on the Ford LiDAR-video driving test data set and will be discussed. To the best of our knowledge the use of multi-modal deep convolutional neural networks for dynamic real-time LiDAR-video registration has not been presented.

1 MOTIVATION

Navigation and situational awareness of optionally manned vehicles requires the integration of multiple sensing modalities such as Light Detection and Ranging (LiDAR) and video, but could just as easily be extended to other modalities including Radio Detection And Ranging (RADAR), Short-Wavelength Infrared (SWIR) and Global Positioning System (GPS). Spatio-temporal registration of information from multi-modal sensors is technically challenging in its own right. For many tasks such as pedestrian and object detection tasks that make use of multiple sensors, decision support methods rest on the assumption of proper registration. Most approaches Bodensteiner & Arens (2012) in LiDAR-video for instance, build separate vision and LiDAR feature extraction methods and identify common anchor points in both. Alternatively, by generating a single feature set on LiDAR, Video and optical flow, it enables the system to to capture mutual information among modalities more efficiently. The ability to dynamically register information from the available data channels for perception related tasks can alleviate the need for anchor points *between* sensor modalities. We see auto-registration as a prerequisite need for operating on multi-modal information with confidence.

Deep neural networks lend themselves in a seamless manner for data fusion on time series data. It has been shown [Ngiam et al. (2011)] for some challenges in which the modalities share significant mutual information, the features generated on the fused information can provide insight that neither input alone can. In effect the ML version of, "the whole is greater than the sum of it's parts".

Autonomous navigation places significant constraints on the speed of perception algorithms and their ability to drive decision making in real-time. Though computationally intensive to train, our implemented DCNN's run easily within our real-time frame rates of 8 fps and could accomodate more standard rates of 30-60 fps. **Is this last statement true given the sped up opt flow? If not, delete it.**

With most research in deep neural networks focused on algorithmic improvements and novel applications, a significant benefit to applied researchers is sometimes under appreciated. The automated feature generation of DNNs enables us to create mutli-modal systems with far less overhead. The

need for domain experts and hand-crafted feature design are lessened, allowing more rapid prototyping and testing.

The generalization of auto-registration across multiple assets is clearly a path to be explored.

In this paper, the main contributions are: (i) formulation of an image registration problem as a fusion of modalities from different sensors, namely LIDAR (L), video (Grayscale or R,G,B) and optical flow (U,V); (ii) performance evaluation of DCNN with various input parameters, such as kernel filter size and different combinations of input channels (R,G,B,Gr,L,U,V); (iii) fusion of patch-level and image-level predictions to generate alignment at the frame-level. The experiments were conducted using a publicly available dataset from FORD and the University of Michigan [Pandey et al. (2011)]. The DCNN implementation was executed on an NVIDIA Tesla K40 GPU with 2880 cores and compute power of 5 TFLOPS (single precision). The paper is organized into the following sections: Section 1 describes the introduction and motivation for this work; Section 2 provides a survey of the related work; the problem formulation along with the dataset description and the preprocessing is explained in Section 3; Section 4 gives the details of the DCNN setup for the different experiments; Section 5 describes the experiments and the post-processing steps for visualizing the qualitative results; finally Section 6 summarizes the paper and conludes with future research thrusts.

2 Previous Work

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A great amount has been published on various multi-modal fusion methods.Ross & Jain (2003),Gregor & LeCun (2011),(2004),(2003),Snoek et al. (2006). The most common approaches taken generate features of interest in each modality separately and create a decision support mechanism that aggregates features across modalities. If spatial alignment is required across modalities, as it is for LiDAR-video such filter methods Thrun (2011) are required to ensure proper inter-modal registration. These filter methods for leveraging 3D LiDAR and 2D images are often geometric in nature and make use of projections between the different data spaces.

The use of deep neural networks to analyze multi-modal sensor inputs has increased sharply in just the last few years, including audio-video Ngiam et al. (2011) Kim et al. (2013), image/text Srivastava & Salakhutdinov (2012), image/depth Lenz et al. (2013) and LiDAR-video To the best of our knowledge the use of multi-modal deep neural networks for dynamic LiDAR-video registration has not been presented.

A common challenge for data fusion methods is deciding at what level features from the differing sensor streams should be brought together. The deep neural network (DNN) approach most similar to the more traditional data fusion methods is to train DNN's independently on sensor modalities and then use the high-level outputs of those networks as inputs to a subsequent aggregator, which could also be a DNN. This is analogous to the earlier example of learning 3D/2D features and the process of identifying common geometric features.

It is possible however to apply DNN's with a more agnostic view enabling a unified set of features to be learned across multi-modal data. In these cases the input channels aren't differentiated. Unsupervised methods including deep Boltzman machines and deep auto-encoders for learning such joint representations have been successful.

Deep convolutional neural networks (DCNN's) enable a similar agnostic approach to input channels. A significant difference is that target data is required to train them as classifiers. This is the approach chosen by us for automating the registration of LiDAR-video and optical-flow, in which we are combining 1D/3D/2D data representations respectively to learn a unified model across as many as 6D.

3 Problem Statement

Being able to detect and correct the misalignment (registration, calibration) among sensors of the same or different kinds, is critical for decision support systems operating on their fused information streams. For our work DCNN's were implemented for the detection of small spatial misalignments in LiDAR and Video frames. The methodology is directly applicable to temporal registration as

well. LiDAR-video data collected from a driverless car was chosen for the multi-modal fusion test case. LiDAR-video is a common combination for providing perception capabilities to many types of ground and airborne platforms including driverless cars Thrun (2011).

3.1 FORD LIDAR-VIDEO DATASET AND EXPERIMENTAL SETUP

Figure 1: Left: The modified Ford F-250 pickup truck. Right: Sample image from front facing camera and green dots indicate the region of LiDAR data.

The FORD LiDAR-video dataset **?** is collected by an autonomous Ford F-250 vehicle integrated with the following perception and navigation sensors as shown in Figure 1:

- Velodyne HDL-64E LiDAR with two blocks of lasers spinning at 10 Hz and a maximum range of 120m.
- Point Grey Ladybug3 omni-directional camera system with six 2-Mega-pixel cameras collecting video data at 8fps with 1600×1600 resolution.
- Two Riegl LMS-Q120 LIDAR sensors installed in the front of the vehicle generating range and intensity data when the laser sweeps its 80°field of view (FOV).
- Applanix POS-LV420 INS with Trimble GPS system providing the 6 degrees of freedom (DOF) estimates at 100 Hz.
- Xsens MTi-G sensor consisting of accelerometer, gyroscope, magnetometer, integrated GPS receiver, static pressure sensor and temperature sensor. It measures the GPS coordinates of the vehicle and also provides the 3D velocity and 3D rate of turn.

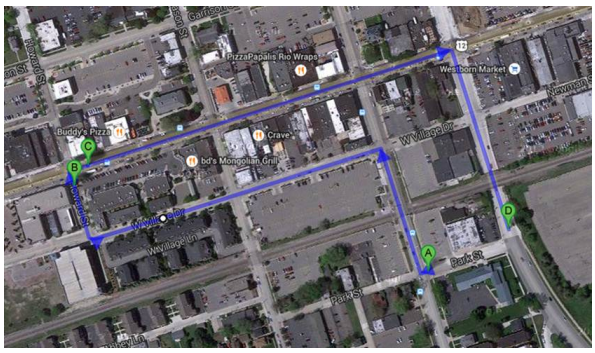


Figure 2: Training (A to B) and testing (C to D) tracks in the downtown Dearborn Michigan.

This dataset is generated by the vehicle while driving in and around the Ford research campus and downtown Michigan. The data includes feature rich downtown areas as well as featureless empty parking lots. As shown in Figure 2, we divided the data set into training and testing sections A to B and C to D respectively. They were chosen in a manner that minimizes the likelihood of contamination between training and testing. Because of this, the direction of the light source is never the same in the testing and training sets.

3.2 Optical Flow

Figure 3: Optical flow: Hue indicates orientation and saturation indicates magnitude

In the area of navigation of mobile robots, optical flow has been widely used to estimate egomotion [Prazdny (1980)], depth maps [Shahraray & Brown (1988)], reconstruct dynamic 3D scene depth [Yang et al. (2012)], and segment moving objects [Chien et al. (2002)]. Optical flow provides information of the scene dynamics and is expressed as an estimate of velocity at each pixel from two consecutive frames, denoted by $\vec{u}$ and $\vec{v}$. The motion field from these two frames is measured by the motion of the pixel brightness pattern, where the changes in image brightness is due to the camera or object motion. Liu (2009) describes an algorithm for computing optical flow from images, which is used during the preprocessing step. Figure 3 shows an example of the optical flow computed using two consecutive frames from the Ford LiDAR-video dataset. By including optical flow as input channels, we imbue the DCNN with information on the dynamics observed across time steps.

3.3 Preprocessing

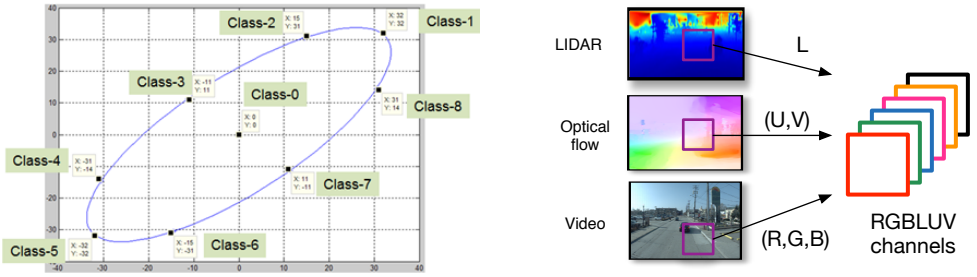
At each video frame timestep, the inputs to our model consist of *C* channels of data with *C* ranging from 3-6 channels. Channels consist of grayscale *Gr* or *(R,G,B)* information from the video, horizontal and vertical components of optical flow *(U,V)* and depth information *L* from LiDAR The data from each modality is reshaped to a fixed size of 800×256 values, which are partitioned into $p \times p$ patches at a prescribed stride. Each patch $p \times p$ is stacked across *C* channels, effectively generating a vector of *C* dimensions. The different preprocessing parameters are denoted by patch size *p*, stride *s* and the number of input channels *C*.

Preprocessing is repeated *N* times, where *N* is the number of offset classes. For each offset class, the video (R,G,B) and optical flow (U,V) channels are kept static and the depth (L) channel from the LiDAR is moved by the offset simulating a misalignment between the video and the LiDAR sensors. In order to accurately detect the misalignment in the LiDAR and Video sensor data, a threshold is set to limit the information available in each channel. The LiDAR data has regions of sparsity and hence the LiDAR patches with a variance ($\sigma^2 < 15\%$) are dropped from the final dataset. This leads to the elimination of the majority of foreground patches in the data set, reducing the size of the training and testing set by approximately 80%. Figure 4(a) shows a $N = 9$ class elliptically distributed set of offsets and Figure 4(b) shows a $p \times p$ patch stacked across all the different *C* channels.

4 Model Description

need to describe the parameters post-processing,classification metric for each patch,a table with common parameters for the experiments would help,voting scheme

Our models for auto-registration are DCNN's trained to classify the current misalignment of the LiDAR-video data streams into one of a predefined set of offsets. DCNN's are probably the most successful deep learning model to date on fielded applications. The fact that the algorithm shares weights in the training phase, results in fewer model parameters and more efficient training. DCNN's are particularly useful for problems in which local structure is important, such as object recognition



(a) Visualization of the elliptically distributed $N = 9$ classes

(b) Stacking of $p \times p$ patch over all the different channels

Figure 4: Preprocessing steps

in images and temporal information for voice recognition. The alternating steps of convolution and pooling **(as depicted in figure X)** generates features at multiple scales which in turn imbues DCNN's with scale invariant characteristics.

The model consists of a 4-layer **?** CNN classifier *see image of network* that estimates the offset between the LiDAR-video inputs at each time step. For each patch within a timestep, there are O variants with the LiDAR-video-optical flow inputs offset by the predetermined amounts. The CNN outputs to a softmax layer, thereby providing an offset classification value for each patch of the frame. figure x: In the 5 class example we color each patch of the frame with a color corresponding to the predicted class.

For each frame a simple voting scheme is used to aggregate the patch level offset predictions to frame level predictions. A sample histogram of the patch level predictions is show in figure x.

5 Experiments and Post-processing

The NVIDIA Kepler series K40 GPUs [NVIDIA Inc. (2012)] are very FLOPS/Watt efficient and are being used to drive real-time image processing capabilities [Venugopal & Kannan (2013)]. These GPUs consist of 2880 cores with 12 GB of on-board device memory (RAM). Deep Learning applications have been targeted on GPUs previously in [Krizhevsky et al. (2012)] and these implementations are memory bound. A GPU with higher memory capacity is excellent for these experiments due to the number of channels that are stacked and provided as the input to the DCNN. The LiDAR-video dataset is augmented with the optical flow information resulting in 6 channels which means that the input to the DCNN is $32 \times 32 \times 6$ per patch. Figure 5 shows the setup used for the DCNN implementation on the GPU, where *C* defines the number of channels.

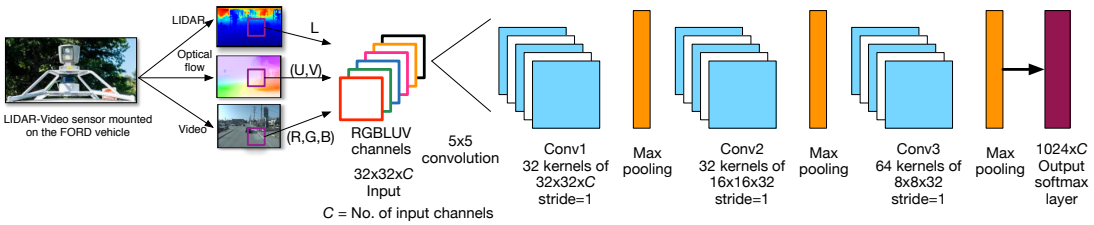


Figure 5: Experimental setup of the LiDAR-video DCNN with 5×5 convolution

Need a complete list of the experiments run images to visualize the frame level results please place any confusion matrices and your comments on what you think the results say. feel free to suggest any tables or other visuals to include.

5.1 5 CLASS TESTS

In our initial tests, the linearly distributed set of 5 offsets of the LiDAR-video data were performed. Table 1 lists the inputs and CNN parameters explored ranked in the order of increasing accuracy **(define accuracy and other cm metrics), include training vs test error and conf mats if room allows**.

As can be seen ...

5.2 9 CLASS TESTS

The subsequent tests were designed to understand whether the simple linear displacement model of the 5-class test could be generalized to a model capable of discriminating multiple directions and displacement magnitude. To achieve this 8 positions were chosen on an ellipse along with it's center **describe the parabola**. LiDAR-video was offset in a manner similar to the 5 class test. Nine training and test sets were generated and an identical patch level CNN was constructed differing only in the 9 class softmax output layer.

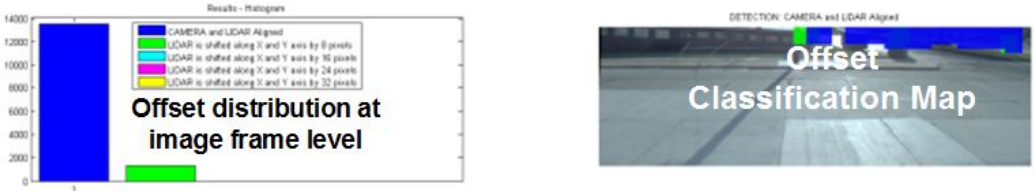


Figure 6: Placeholder: Voting

Table 2 lists the inputs and CNN parameters explored ranked in the order of increasing accuracy **(define accuracy and other cm metrics), include training vs test error and conf mats if room allows**.

Discussion: what results confirmed expectations or surprised us (grey scale). Can we confidently say optical flow improves prediction.

6 CONCLUSIONS AND FUTURE WORK

We did it. We're great.

The next step in taking this work forward is to complete our development of a deep auto-registration method for ground and airborn platforms requiring no apriori calibration ground truth. Our airborne applications in particular present nosier data with an increased number of degrees of freedom. The extension of these methods to simultaneously register information across multiple platforms and larger numbers of modalities will provide interesting challenges that we look forward to working on.

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