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Master Thesis Proposal

Multi-View Temporal Fusion in Semantic Segmentation

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1 Introduction

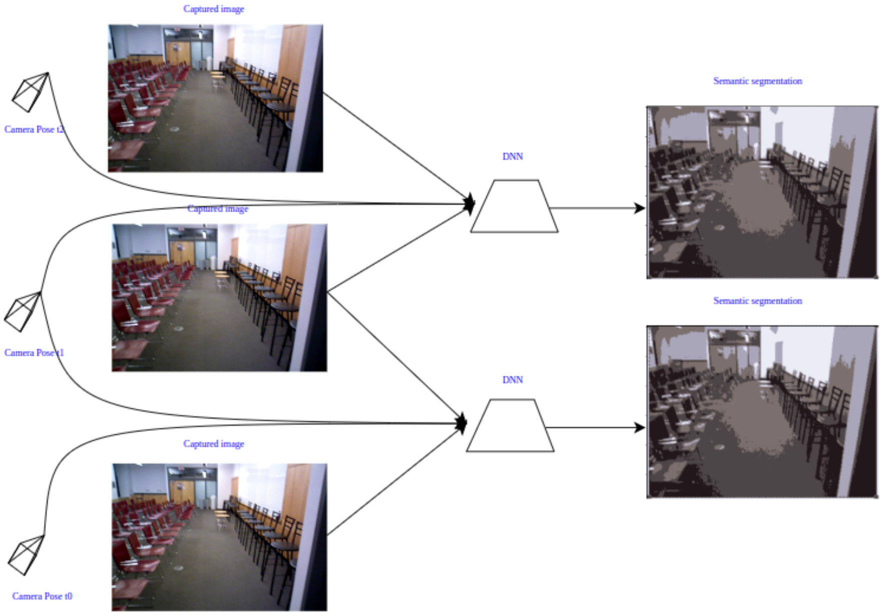


Figure 1: Semantic segmentation from pair of images and pose

Predicting variables of interest at different future timestamps by integrating information at each step from past or other modalities is a common temporal fusion problem. The fusing of information at every step helps optimize the future target prediction. Temporal fusion of information can be observed in classical and deep learning-based architecture. Fusion of information in a temporal fashion is done in both classical and deep learning architecture. An image-pose pair encoder-decoder-based architecture for disparity estimation fuse information in the latent space successively with the help of Gaussian process at the latent space [13]. An end-to-end video-based person re-identification network fuse feature in a spatial-temporal fashion to extract the overlapping information. In this work, both the spatial and temporal features of the input image sequence are calculated by collecting the feature vector $f^{(t)}$ from the convolutional neural network (CNN) that connects the temporal pooling layer. The aggregated feature are formed into a single feature vector that is averaged over the entire sequence [4]. Information can be fused at the single-stage output of a multi-stage encoder-decoder network.

An online multi-view feature prediction network on the posed video frame, with fusing richer scene geometry feature calculated at the last step, is fused into the current step efficiently. Geometric information from the output of the previous encoder-decoder network is fused to compute a cost volume and fed as input to the second stage encoder-decoder architecture. Also, the output of the second stage network is fed back to the convolutional long short-term memory (ConvLSTM) network in the latent space by warping [9].

Computer vision aims to understand the surrounding environment using various mathematical modeling techniques. Moreover, semantic segmentation is the key problem in computer vision that targets complete scene understanding. The semantic segmentation segments the input images based on the semantic information and categorizes each pixel into a class from the list of labels [24]. Semantic segmentation can be applied to 2D images, volumetric data, or video. Number of field take advantage of understanding the surrounding environment such as human-machine interaction [27], computational photography [40], image search engines [35], augmented reality [19], autonomous driving [34], biomedical imaging [2], fashion [39]. Traditional semantic segmentation is performed with conditional random fields [28], clustering [7]. With the development of deep learning architecture, semantic segmentation problem are solved with CNN's [26], [5], [12]. A segmentation network can be thought of as an encoder-decoder network, usually with a pre-trained classification network on the encoder side followed by semantically projecting the learned discriminative feature onto the feature space to get a dense classification.

A general framework of semantic segmentation involves independently applying a deep image segmentation model to every image in a sequence. However, these approaches result in information loss by not considering the correlation among the consecutive frames. The data loss problem is tackled by taking the information from the previous step is fusing at the current step in a timely manner resulting in an efficient semantic segmentation. Estimation of semantic segmentation from unconstrained monocular camera images is a challenging task. State of the art temporal semantic segmentation is based on deep learning. A temporally distributed network designed for semantic segmentation finds the correlation between the frames and the attention propagation module, effectively combining the distributed feature groups [15]. Efficient semantic segmentation can be performed by fusing current, and the previous camera poses information onto the latent space in an encoder-decoder-based architecture.

This thesis aims to study the state-of-the-art temporal fusion techniques and compare the results from these findings. Furthermore, cross-transfer the temporal fusion technique to the segmentation task by fusing information from the previous step to the current step to extract the correlation between the frames and optimize the prediction at every time stamp.

2 Problem Statement

Multi-view temporal fusion in the context of images is a field that targets fusing the temporal information at every step to extract the temporal correlation between the consecutive frames to optimize the prediction at each time stamp. Different fields use temporal fusion to optimize the prediction, and one such field is the segmentation task. Semantic segmentation aims to label each pixel in an image, and it is an ill-posed problem. Over the past years, many algorithms and architectures have been proposed to find the semantic segmentation of the scenes. Conventional semantic segmentation algorithms compute semantic maps for the individual frame. They do not consider the geometric correlation between the consecutive frames, thereby losing crucial overlapping information in the successive images. Images can be obtained from a stereo camera or a monocular camera. Estimation of semantic segmentation from the unconstrained monocular camera image is a challenging task. However, there are potential benefits to using monocular camera images. Firstly, it reduced cost and flexibility in the movement of the monocular camera, thereby gathering rich information about the surrounding environment. Secondly, multiple varying point images can fuse all the information for robust and stable semantic segmentation in a temporal fashion. Most of the state-of-the-art semantic segmentation architecture is computationally heavy. Therefore an excellent lightweight architecture with acceptable performance needs to be developed. This work concentrates on the literature survey of state-of-the-art temporal fusion techniques, comparing results from these findings, and cross-transfer of temporal fusion techniques to the segmentation task. Finally, end the thesis with the deployment of the model on a low computational android device.

3 Related Work

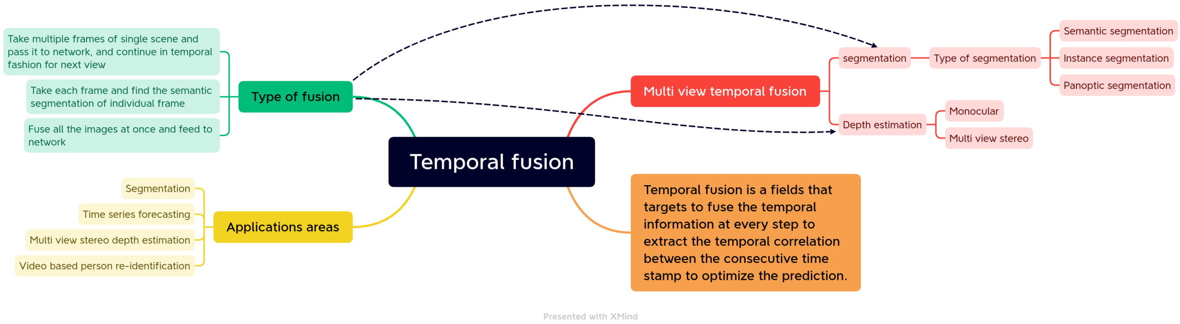

Take multiple frames of single scene and pass it to network, and continue in temporal fashion for next view
Take each frame and find the semantic segmentation of individual frame
Fuse all the images at once and feed to network
Type of fusion
Segmentation
Time series forecasting
Multi view stereo depth estimation
Video based person re-identification
Applications areas
Temporal fusion
Multi view temporal fusion
segmentation
Type of segmentation
Semantic segmentation
Instance segmentation
Panoptic segmentation
Depth estimation
Monocular
Multi view stereo
Temporal fusion is a fields that targets to fuse the temporal information at every step to extract the temporal correlation between the consecutive time stamp to optimize the prediction.
Presented with XMind

Figure 2: Multi view stereo mind map

Temporal fusion is a technique to fuse the gathered information in the time axis, making the model robust and reliable. The rich correlation between the consecutive data sources is gathered and combined in a temporal fusion fashion. Data collected over time can be fused in several different ways. For example, combine the collected data over time and feed it to the detection module [36]. Fusion can be done at each time stamp; we can take the last step data and pass it onto the prediction module to make the current step prediction efficient [9]. Alternate variant would be fusing at a different location of the prediction model [14], [13], [9]. In stereo vision, the stereo pair is passed onto the pair of ResNet-50, followed by many convolutional layers. The tokens are afterward reassembled in different locations with variable resolution and fused progressively [32]. Number of field take advantage of the fusion technique, such as multi-camera video surveillance [37], myoelectric interfaces to decode the Electromyogram (EMG) time-series data [18], time series forecasting [22], multi-view stereo depth estimation [9], video-based person re-identification [17], [4], segmentation [20], [16], [30].

Multi-view temporal fusion deals explicitly with the fusion of image information taken at different time stamps. Combining the data from consecutive frames makes the following prediction step robust and reliable. Work by Fan Zhu et al. solves the multi-view action recognition problem with a local segment of silhouettes similarity voting scheme followed by a multi-sensor fusion method. This approach gives impressive results by fusing the spatial multi-sensor inputs [41]. A multi-view summarization work by Yanwei Fu et al. consumes a large number of video files and finds the critical information quickly from these data by representing the multi-view video structure with a Spatio-temporal shot graph since it carries the information of the shots and at the same time find the correlation among the shots [10]. A real-time texture montage for dynamic multi-view reconstruction uses the dilated depth discontinuities and majority voting from Holoportation to suppress the ghosting effect while blending textures. Sudden change in the viewpoint results in the rapid change of texture weight fields. A temporal texture weight is deployed to accommodate the smooth transition of texture weights [8]. An online-based multi-view depth prediction approach on the posed video streams propagates the scene geometry information computed in the previous step onto the current step in a geometrically feasible way. A lightweight encoder-decoder architecture with the cost volume computed from the pair of images with ConvLSTM at the latent space to accommodate the past information in the current step [9]. Minghan Li et al. proposed an effective one-stage video segmentation architecture spatially calibrated with STMask temporal fusion in the pipeline. The temporal correlation between the video frames is captured with STMask to find the instance mask for the current frame from the adjacent frame. Thereby solving the motion blur and partial occlusion problem [21].

Segmentation is one of the sub-problems of the computer vision domain to classify the pixels or segments of an image into a particular class. Image segmentation is a super-set of image classification by detecting the objects and specifying the location of objects present in the image. Traditional segmentation methods used region growing and snake algorithms to compare the pixel values to get the segment map. The advent of deep learning-based architecture in computer vision pushed the accuracy and performance of the segmentation task. Image segmentation can be broadly classified into the semantic, instance, and Panoptic. Semantic segmentation is a task of classification of pixels in an image into a semantically meaningful class [23]. Instance segmentation is a method that classifies the pixel based on instances rather than classes. Panoptic segmentation is a task that can be expressed as a combination of semantic and instance segmentation. In this, each segment class is identified.

Different fields use semantic segmentation, such as unmanned aerial vehicles

(UAV), Autonomous robots, medical imaging and diagnosis, and facial recognition. Classical semantic segmentation is based on the decision trees [31] or Markov random fields [38]. Ciresan et al. [6] suggested a CNN-based semantic segmentation architecture on a biological image. Long et al. developed an efficient fully convolutional network (FCN) segmentation network that generated dense prediction of images of any size much faster than any previously developed method. The success of FCN paved the way for the development of efficient segmentation architecture. In the context of medical imaging, a state-of-the-art encoder-decoder-based semantic architecture was developed named U-Net [29]. The spatial dimension is reduced on the encoder side to find what information to capture, and the same is up-sampled using the decoder to find the where information. Following years a similar architecture to U-Net known as SegNet [1] was introduced. Furthermore, it does not transfer feature maps from the encoder to the decoder entirely. Instead, transfer only the max-pooling indices [3]. Yi Zhu et al. work on improving the semantic segmentation via joint image-label propagation to scale up the training set. Given a sequence of video frames with labels for only a subset of frames, the model's ability to segment is exploited to predict the unlabelled frames by label propagation, and joint label propagation [42]. A video segmentation technique that makes use of temporal coherence in video and reuses single-stage image segmentation using a NetWarp module is proposed by Raghudeep Gadde et al. [11]. The filter representation of the present image is changed by the respective representation in the previous frame by NetWarp. There was a lot of work related to the semantic segmentation, however, the problem of temporal fusion of camera pose with semantic segmentation is rarely addressed. NYU-Depth v2 [25] is a video sequence from a variety of indoor scenes recorded by the RGB and depth camera. The dataset contains a densely labeled pair of RGB and depth images. The roll, yaw, pitch, and tilt angle of the accelerometer device are captured during each frame. The intrinsic camera parameter of the camera is also provided. Annotation tool [33] can be used to create a small dataset for the evaluation purpose. Transfer learning of semantic segmentation models can also be performed to start from a baseline with a focus on real-time application. This thesis work aims to incorporate the camera's pose temporally to learn the overlapping geometric information from the consecutive image frames to improve semantic segmentation prediction efficiently.

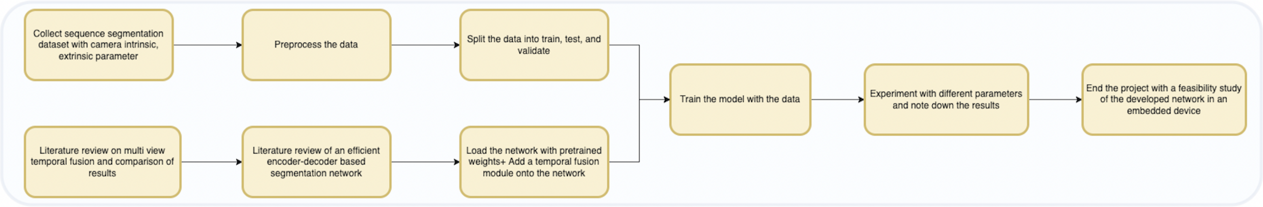

Collect sequence segmentation dataset with camera intrinsic, extrinsic parameter
Preprocess the data
Split the data into train, test, and validate
Literature review on multi view temporal fusion and comparison of results
Literature review of an efficient encoder-decoder based segmentation network
Load the network with pretrained weights+ Add a temporal fusion module onto the network
Train the model with the data
Experiment with different parameters and note down the results
End the project with a feasibility study of the developed network in an embedded device

Figure 3: Pipeline of master thesis project

4 Research questions

Three research questions are defined for the master thesis

RQ1 What are the works on state-of-the-art temporal fusion?

RQ2 How are the results from RQ1 compared with each other to perform temporal fusion?

RQ2.1 What are the results in comparison with different error metrics?

RQ3 How to cross-transfer the temporal fusion technique to the other tasks, such as object detection or semantic segmentation?

RQ3.1 How different loss criteria impact the performance of the semantic segmentation?

RQ3.2 What is the performance of semantic segmentation with respect to different Gaussian kernels?

5 Project Plan

The following sections explain work packages, milestones and project schedules, and deliverables.

5.1 Work Packages

The bare minimum will include the following packages:

WP1 Literature Search
This section aims to search for references to papers related to multi-view stereo.

T1.1 Literature review
This task collection of literature related to multi-view stereo is done, and conceptual understanding of the 3D geometry from images.

WP2 Data aggregation and preprocessing
This section explains the data collection and data preprocessing.

T2.1 Data collection
In this section, data is collected from multiple sources, and the nature of the data is examined and analyzed using visualization tools or statistical methods. An analysis is carried out to ensure data is diverse, unbiased, and abundant in nature.

T2.2 Data preprocessing
Preprocessing of data is carried out based on the input requirement of the model. The preprocessing step converts the raw sourced data into a format that enables successful model training.

WP3 Model implementation
This section explains the development and implementation of the model.

T3.1 Evaluation of the model

This task aims to reproduce the Multi-view Stereo by Temporal Nonparametric Fusion architecture results.

T3.2 Cross application of the temporal fusion to the segmentation
In this section, the extension of temporal fusion architecture to the other application areas of computer vision is carried out.

WP4 Evaluation
This package aims to evaluate the results based on the different metrics.

T4.1 Results reporting
In this task, the output of the Evaluation is reported.

WP5 Project Report
This work package involves writing the project report. It is done in parallel with all previous work packages.

T5.1 Documentation of reviewed literature
In this task, a detailed analysis of the state of the art is done and all the findings are documented in the project report.

T5.2 Documentation of baseline results
In this task, the implementation result of the Temporal Fusion baseline is done.

T5.3 Documentation on the results for the different temporal fusion This task documents the result of different temporal fusion architectures with different error metrics.

T5.4 Documentation of cross-domain application of temporal fusion approach
In this task, the result of the cross-domain application of the temporal fusion approach is performed.

5.2 Milestones

M1 Literature search

M2 Data collection and preprocessing

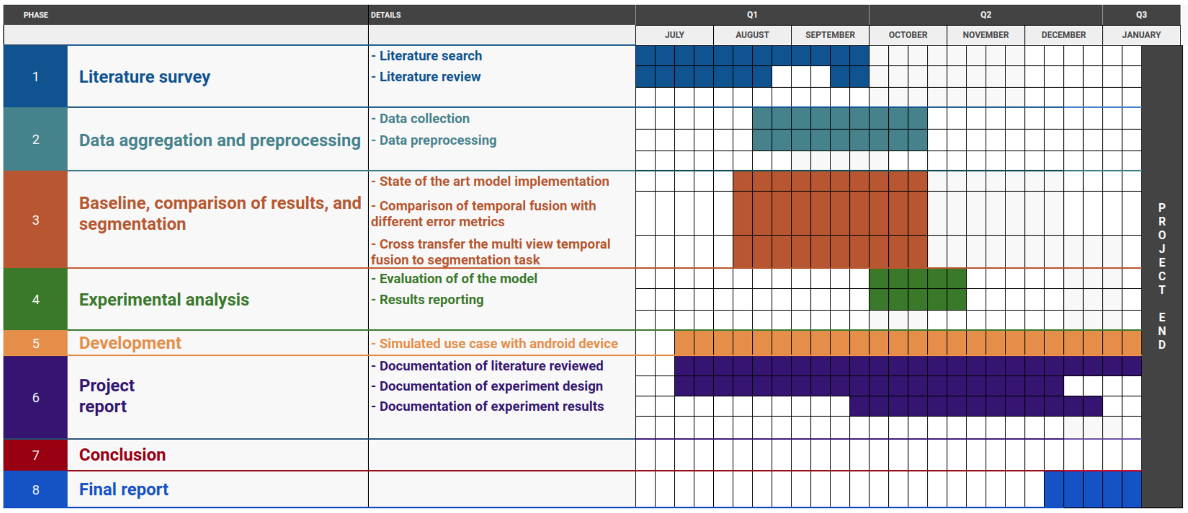
M3 Building a baseline

M4 Experimental Analysis

M5 Development

M6 Report submission

5.3 Project Schedule



PHASE		DETAILS
1	Literature survey	- Literature search - Literature review
2	Data aggregation and preprocessing	- Data collection - Data preprocessing
3	Baseline, comparison of results, and segmentation	- State of the art model implementation - Comparison of temporal fusion with different error metrics - Cross transfer the multi view temporal fusion to segmentation task
4	Experimental analysis	- Evaluation of of the model - Results reporting
5	Development	- Simulated use case with android device
6	Project report	- Documentation of literature reviewed - Documentation of experiment design - Documentation of experiment results
7	Conclusion	
8	Final report	

Figure 4: Timeline of the project

5.4 Deliverables

Minimum viable

- Literature review on the temporal fusion in the context of depth estimation and semantic segmentation
- Analysis of the state of the art temporal fusion architectures
- Create a baseline of temporal fusion with images from a monocular camera

Expected

- Compare performances of state of the art temporal fusion techniques with different error metrics
- Cross transfer the temporal fusion architecture to the segmentation task
- Simple simulated use case of temporal fusion on the android device

Maximum

- Evaluation of the temporal segmentation method with different loss criteria
- Improved monocular image multi-view temporal fusion technique
- Performance of multi-view temporal fusion for different Gaussian kernels

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