

Major Technical Project (MTP) - 2017 School of Computing & Electrical Engineering IIT Mandi Kamand Himachal Pradesh MTP Coordinators

Dr. Arnav Bhavsar (arnav@iitmandi.ac.in) Dr. Samar Agnihotri (samar@iitmandi.ac.in)





















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Introduction

- Network Coding is a networking technique in which transmitted data is encoded and decoded to increase the network throughput, reduce delays and make the network more robust.
- It increases the throughput(capacity) of a network and it is useful to know the bound on the throughput that can be achieved using this technique.
- There are many bounds existing in theory, such as geometrical bound, graphical bound which require high computational effort as mentioned in [1].
- In [1], [2], theory and algorithms which reduces the computational effort of computing graphical bounds are developed. The algorithms which reduce the computational effort to find the capacity bounds developed in above mentioned papers are to be implemented effectively.

Objective

- The algorithms AllMaxSetsC in [1], is implemented along with Procedure B and Procedure C in [1] as part of internship by few of my colleagues.
- Our objective is to start from this point and implement other algorithms which are AllIrrSets(computation of all irreducible sets), ReducedLPEq(in [2]) and ReducedLPIneq(in [2]) in an efficient way and design new algorithm which is efficient than previous if possible.
- The output of the AllMaxSetsC and AllIrrSets is given as input to the other two algorithms in [2]to get the final result.

Algorithm implementation for Computation of Network Coding Capacity Bounds Toyaz Sai Madhav, Thejas Babu Dr.Satyajit Thakor

Network Coding Capacity Bound

Polymatroid Function:

A function $h: 2^X \to R$ is *polymatroidal* if it satisfies the following axioms for all disjoint A, $B \subseteq X$

$$h(A \mid X \setminus \{A\}) \ge 0, A \in X \quad (1a)$$

$$I(A; B \mid C) \ge 0, A \neq B; C \subseteq X \setminus \{A, B\} \quad (1b)$$

- The above are the polymatroidal inequalities along with constraints C1, C2, C3, C4 in [1] characterise the network coding capacity region.
- Some of the inequalities 1a, 1b may become redundant when above contraints are imposed.
- Hence these redundant inequalities removal reduces number of inequalities and dimensions.



IIT MANDI

Butterfly Network





Above shown is the butterfly network along with which network coding working principle is depicted.

- Alg Redu Equ
- Alg
- Redu Eqι

- 2016.

Results

gortihm Used	Inequalities	Dimensions		
	Reduction($\%$)	$\operatorname{Reduction}(\%)$		
_	4617(0%)	512(0%)		
$\operatorname{acedLpIneq}([2])$	760(83.54%)	54(92.38%)		
uivalence class	329(92.87%)	40(92.19%)		
le 1. Butterfly network Results(Correlated Sources)				

gortihm Used	Inequalities	Dimensions		
	$\operatorname{Reduction}(\%)$	Reduction($\%$)		
_	4617(0%)	512(0%)		
$\operatorname{icedLpIneq}([2])$	449(90.28%)	39(95.31%)		
uvalence class	115(97.51%)	19(96.29%)		
e 2: Butterfly network Results(Independent Sources)				

• Some random graphs are generated by using approach used in [4] and more simulation results are generated by processing these networks • These simulation networks FDG's nodes vary from 5 to 15.

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Automated Discrimination of Dicentric and Monocentric Chromosomes



Onkar Singh, Swapnil Sharma and Dr. A. K. Sao

OBJECTIVE

- Evaluate cell slides efficiency for further computation.
- To segment chromosomes from a given cell slide.
- To identify dicentric chromosomes present in a cell slide.



MOTIVATION

- Radiation exposure is harmful.
- Medication of radiation depends on accurate assessment of absorbed radiation dose.
- The only validated method to estimate radiation dosage is dicentric chromosomal assay.
- An individual can complete one slide of metaphases manually in 1-2 days working 7-8 hours/day.

APPROACH





Classification Methodology Linear Classifier (SVM) Feature extraction Methodology Gradient Vector Field Snake (Curve Estimation) Discrete Curve Evolution (Centreline Estimation) Intensity Integrate Laplacian (Width Estimation) Neural Network Classifier Convolutional Neural Network



RESULTS





Segmented DCs

Feature Plot for DCs and MCs

PROBLEMS





Sister Chromatid Separation

Poor metaphase slides and poor quality images

FUTURE WORK

- Statistical evaluation using huge corpus
- Feature selection can be further enhanced to incorporate better distinction.
- DNN framework can be explored for detection and segmentation

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Ball Tracking, Event Detection, Video Summarization of Football Vishwa Mangal Mentor: Dr. Aditya Nigam



- On testing with two class i.e forehand and backhand, we got the 100% accuracy.
 On the time of the test of test o
- On testing with three class we got the accuracy of 70%.

• Manually classified frames into

• 30 instances each of forehand, backhand, and service.

Working Of YOLO

YOU ONLY LOOK ONCE

forehand, backhand, service.



Using Deconvnet to extract regions learned implicitly by CNN from bird images Aswin A (B13305) Mentors: Dr. Arnav Bhavsar, Dr. Dileep A. D. School of Computing and Electrical Engineering, Indian Institute of Technology, Mandi

Abstract

Identification of regions of the object plays an important role in the task of fine-grained classification. For classifying birds, various regions of birds such as head, body, leg, tail, etc. have to be identified. Filters of higher level layers of CNN trained to classify different species of birds implicitly learn regions of the birds mentioned above. Identification of these filters can be achieved with the help of deconvnet [1]. Using the deconvolution image outputted by deconvnet, regions of birds are extracted from bird images. Caltech-UCSD Birds-200-2011[2] dataset is used for the evaluation of our method.

Keywords: fine-grained, region identification, deconvolution

Introduction

Fine-grained recognition of objects is a challenging problem in the field of computer vision and is becoming increasingly popular. The overall structure of objects is almost similar in fine-grained classification. This problem is addressed by humans by looking at the minute variation in different parts of the object. Similar methodology is followed in this work and as a first step, regions of the birds are extracted from bird images which will be used to identify minute differences between bird species.

Convolutional Neural Network

An image is classified into its species using Convolutional Neural Network (CNN).

- Architecture VGG19 [3]
- Weights fine tuned for Caltech-UCSD dataset [2]
- Features from pool5 and fc7 layers
- Linear SVM

Input Features	Accuracy (%)
pool5	76.7
fc7	77.9

Performance on species classification. Table 1:



Figure 1: Complete process of region extraction from bird images. During training, deconvolution images and segmentations are used to calculate filter scores for selecting set of filters corresponding to a region. Using the deconvolution image of the highest activated filter from the set of filters for a region, the region from the input image can be extracted for a test image.

Deconvolution

Deconvolution is a technique used for understanding the learnings of CNN.

- Activations of intermediate layers are mapped back to input pixel space
- Shows input patters responsible for activations of a feature map



Figure 2: Top deconvolution images along with original image patches for randomly selected filters in *pool*4 layer of VGG net.

Deconvolution can be achieved through a neural network architecture known as Deconvolution Network (deconvnet) [1] [4].

- Attached to target feature map
- Performs three operations to reconstruct the activity of layer beneath:
 - unpooling
 - rectification
 - filtering
- Repeated until the input layer is reached

- from top deconvolution images
- Feature maps learn different region observed
- Set of filters learn a region



Region Extraction

- Implicitly learned regions can be extracted using deconvolution technique.
- Deconvolution image and saliency map used for scoring filters
- For identifying filters corresponding to a region,
 - deconvolution image from a filter is obtained
 - pixel wise multiplication of deconvolution image and the saliency map of the region
 - summed over all values to get the filter score
- Filter scores will be large for feature maps which learn details about the focused region.

Figure 3: Top deconvolution images along with original image patches of the highest scored filters for different regions of bird in *pool*5 layer of VGG net.

From the regions extracted, descriptions of bird parts corresponding to different regions can be extracted. These descriptions can be used for classification of birds into their species. This can be observed from the distribution of descriptions among all species of birds as shown in Figure 4. The proposed method is extremely suitable for bird species recognition due to its analogy with identification methodology followed by ornithologists and allows for recognition of birds with only part descriptions.



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Future Works

Figure 4: Distribution of descriptions among all species of birds.

References



INTRODUCTION

Acoustic communication in birds is quite rich and is one of the primary ways in which birds make their presence known to each other, as well as this is the most direct way for humans to detect them, often at times when they are difficult to see. Therefore there is a great need for increased use and further development of automated analysis of avian sounds.

BIRD PHRASES

Bird Songs typically comprise a sequence of smaller units, termed phrases, which are separated from each other by longer pauses(silences).

- Need to preserve sequence information associated in the production of the bird songs.
- Automatic phrase recognition system challenging due to noisy environments and limited training data.
- Sparse-Representation(SR) and Support Vector Machines (SVM) have been previously used.
- Dynamic kernel based SVMs have performed considerably well in classifying bird species. Also HMM-based dynamic kernels have been used for speaker recognition tasks. This motivates us to use them for bird phrase

classification as well.

DATASET DESCRIPTION



Cassin's Vireo

Bird phrases were obtained song from recordings of male cassinii). CAVIs(Vireo file was Each sound 16-bit, recorded 1**n** mono, 44.1 kHz sampling rate.

There are two collections of bird phrase data, viz. cassins_1, with 45 phrase classes and cassins_2, with 97 phrase classes. The number of clips per phrase class vary from 2 to 42 in cassins_1, and from 1 to 160 in cassins_2. A total of 36 *phrase classes* and later a set of 22 common phrase classes in common from cassins_1 and cassins_2 were considered for classification. For our classification purposes, cassins_1 is being used for training, and cassins_2 for testing. MFCC features were extracted from each file with frame size=20ms and frame shift=10ms.

BIRD PHRASE CLASSIFICATION USING AUDIO SIGNALS

Guide: Dr. Padmanabhan Rajan & Dr. Dileep A.D.

School of Computing and Electrical Engineering, IIT Mandi

MFCC FEATURE EXTRACTION



In Mel Frequency Cepstral Coefficients(MFCC) feature extraction, each recording is divided into small windows, where speech is assumed stationary. Short-time analysis is performed on each frame as shown in above figure.

KNN USING DTW DISTANCES



k	Accuracy
2	60.85
4	53.97
5	59.08
6	58.11

Classification accuracies of 36 common bird phrases using kNN with DTW distances.

A hidden Markov model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. Continuous-density Hidden Markov Models(CDHMMs) using Gaussian mixture emissions were implemented using *hmmlearn*.

GMM-HMMs were then built to classify bird phrases of 36 classes (common phrases from cassins_1 and cassins_2) by training from cassins_1 and testing from cassins_2. The data could be classified with an accuracy of 58-63% as shown in Table 1.

Number of HMM states	Number of GMM mixtures				
	3 4 5				
3	85.59	85.06	84.54		
4	85.85	85.98	82.7		
5	85.72	82.57	83.36		
Table 2					

HMM-BASED INTERMEDIATE MATCHING KERNEL (HIMK)



Fig. 6.2: Illustration of construction of CSHIMK between a pair of sequences of feature vectors \mathbf{X}_m and \mathbf{X}_n . A 3-state left-to-right HMM with a 3-component GMM for each state is considered in the illustration. The Ψ_i denotes the GMM for state *i* and \mathbf{v}_a^i denotes the qth component of Ψ_i . The feature vectors for matching are selected using the values of $R_{ia}(\mathbf{x}_t|\mathbf{X},\lambda).$

Number of HMM states	Numbe	r of GMM n	nixtures
	3	4	5
3	86.64	86.64	86.91
4	86.52	82.72	81.28
5	86.78 —		

The GMM-based IMK is more suitable where the examples are represented as sets of feature vectors. Since it does not preserve the sequence information while matching the examples, the GMM-based IMK is not preferable to use in sequential pattern classification systems. The HMM models built for 22 phrase classes using *htk* are used for classification in HIMK-based SVM. The SVMs were built using one-vs-rest in LIBSVM.

Gaussian radical basis function (RBF) kernel will be used as the base kernel. For multi-class pattern classification, the HIMK-based SVM models are built in one-against-the-rest class manner. An input test example will be passed into every SVM and will be classified by the *winner-takes-all* strategy which has the maximum discriminant score.

HITESH TARANI (B13139)

HIDDEN MARKOV MODELS(HMM)

There is no support of **Left-to-Right HMMs** in *hmmlearn*. However, for HIMK to preserve sequence of feature vectors, we need to use Left-to-Right HMMs only. So Hidden Markov Model Toolkit (HTK) were used for building them. Left-to-Right HMMs were then built for 22 phrase classes, having at least 10 examples per class. The maximum accuracy obtained was around 86%.

CONCLUSION

REFERENCES

Markov Model $(1)^{a_{12}}(2)^{a_{23}}(3)^{a_{34}}(4)^{a_{45}}(5)$ Acoustic Vector Sequence $b_2(x_1)$, $b_2(x_2)$, $b_3(x_3)$, $b_4(x_4)$, $b_4(x_5)$

Probabilistic parameters of an Hidden Markov Model

Number of HMM states	Number of GMM mixtures		
	3	4	5
3	59.79	62.87	62.1
4	62.34	60.85	58.73
5	63.23	58.29	59.24

Table 1

• kNN using Dynamic Time Warping(DTW) distances perform slightly lower to HMMs.

• Limiting phrase classes with at least 10 examples greatly improved the performance.

• HIMK-based SVMs perform similar to HMMs. • Results obtained are very close to state-of-theart techniques, viz. Sparse Representation(SR) and Support Vector Machines(SVM), which have an accuracy of 85-90%.

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Bird Species Classification Using Audio Signals

INTRODUCTION

Communication through **speech** in case of birds is quite elaborate and important just like human beings. This is also an important because this helps bird know the location of other birds and communicate with them, e.g. giving out a distress call. Within the Avian subclass there are about **10,000** bird species and the automatic recognition of these bird species is called **Bird Classification**.

There are a total of **209 species** found in and around the **Great Himalayan National Park(GHNP)** out of these we are considering **26** prominent bird species for our project.

SCOPE OF WORK

The main focus of our work is to explore state-of-the-art techniques applied to speech and **audio signals** for representing bird calls and for their classification.

The techniques we have used for the bird species classification:

- CNN with Mel filter-bank Energy Coefficients(MFEC) features.
- CNN with raw data(samples itself).

We compare our results with **DNNs**. We also try to visualize the filters learned by the CNN for both the approaches.

CNN ARCHITECTURE USED



The network is composed of **filter stage** followed by a **classification stage**. The filter stage consists of one or more **Convolution layers** with variable number of filters used and one or more **Pooling layers**. The classification stage consists of one or more **fully connected layers** followed by a **Softmax layer**.

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Ayush Garg (B13111) Guide:- Dr. Padmanabhan Rajan & Dr. A.D. Dileep School Of Computing And Electrical Engineering, IIT Mandi





BIRD SPECIES

Table 1: Database of bird calls. The total training data for each species is approximately 14 minutes long.

Bird Species	Number of samples for training	Number of samples for test
Lesser Cuckoo	7	3
Black Throated Tit	8	12
Black and Yellow Grosbeak	10	12
Blackcrested Tit	5	9
Chestnut-crowned Laughingthrush	8	11
Eurasian Treecreeper	9	5
Golden Bushrobin	10	14
Great Barbet	10	20
Grey Bellied Cuckoo	10	7
Grey Bushchat	8	9
Greyhooded Warbler	7	3
Greywinged Blackbird	4	6
Himalayan Monal	11	25
Large-billed Crow	7	4
Orange-flanked Bushrobin	8	10
Oriental Cuckoo	9	7
Pale-rumped Warbler	6	6
Rock Bunting	6	7
Rufous-gorgetted Flycatcher	9	8
Rufous-bellied Niltava	9	9
Russet-backed Sparrow	14	38
Spotted Nutcracker	19	31
Streaked Laughingthrush	9	4
Western Tragopan	8	5
White-cheeked Nuthatch	10	52
Yellow-bellied Fantail	11	12

MFEC FEATURES

Extracting Mel Filter Bank Energy Coefficients (MFEC) is quite similar to the process of extracting MFCC features that are conventionally used. The MFCC features when used with CNN present a major problem because the discrete cosine transform projects the spectral energies into a new basis that may not maintain locality. Hence, we use log-energy computed Mel Filter Bank Energy Coefficients (MFEC) without the use of Discrete Cosine Transform (DCT).

MFEC features are commonly derived as follows:

- Take the Fourier transform of a signal (windowed).
- Map the powers of the spectrum obtained from above onto the mel scale, using triangular overlapping windows.
- Take the logs of the powers at each of the mel frequencies.

CNN WITH MFEC FEATURES

Representation of Data

- The avian sounds are each 44.1 KHz data.
- These audio signals are split into frames of 20ms each with a shift of 10ms.
- The context windows consisting of 15 such sequential frames taken at once.
- MFEC features are extracted from each frame and concatenated to form the context windows.

Architecture Used with MFEC features

- 1 convolution layer with window size of 5X15 and number of filters as 160.
- This is followed by one max pooling layer.
- The fully connected layer has 256 nodes.

Architecture Used with Raw data

- First convolution layer with window size 5X15 and 64 filters.
- Second convolution layer with window size 5X1 and 192 filters.
- Each convolution layer is followed by one max pooling layer.
- Then the fully connected layer again has 256 nodes.

Results

Table 2: Accuracy obtained using CNN for bird species classification with log MFEC features and raw data.

Input	32-MFEC	40-MFEC	48-MFEC	Raw Data
Accuracy	98.48	97.87	98.48	95.74

COMPARISON WITH DNN RESULTS

The DNN has been used conventionally for bird species classification. The following are the results from the Deep's paper using DNN on the bird species data.

Table 3: Accuracy obtained by using DNN for bird species classification with MFCC and log MFEC features.

Hidden Layers	Hidden Nodes	MFCC	log MFEC
	256	95.44	97.17
2	512	96.05	98.18
	1024	95.74	98.18
	256	96.35	97.42
3	512	96.65	98.48
	1024	96.35	98.18

CONCLUSION

We observed that CNN is a good approach for bird species classification giving up to 98.48% accuracy using MFEC features and also giving 95.74% accuracy with raw data. Therefore, we observe that CNN performs quite well even with the raw data itself which motivates us to think that CNNs can be applied on to spectrogram images extracted from bird audio signals. Also, CNNs and DNNs may be applied to a noisy dataset to realize which technique is better for noisy datasets.

Benchmarking Database systems for developing efficient spatial and non-spatial querying framework for astronomical databases

By: Ayush Yadav Mentors: Dr. Sriram Kailasam (IIT Mandi), Dr. Ivelina Momcheva (STScl)

mongo

Objective

1. Compile a comprehensive list of spatial, range and search queries to benchmark based on the recent use by the scientific community

2. Evaluate performance for spatial, range and search queries on different databases and benchmark the results.

3. Identify specifications of the future frameworks for astronomical query processing.

Table 3.2: Performance for Search Queries on different databases

Search Query Performance Mean (s) Min (s) Max (s)

SQL Druid

MongoDB

MongoDB (Sharded)

0.0341

0.0333

0.0011

0.0306 0.0407

0.0040

1.8003

0.0009

1.4430

0.0023

1.8712 2.1201

Results

Work Done

1. Evaluate the indexing techniques and performance on a single node implementation of PostgreSQL, Druid and MongoDb for spatial, non-spatial and range queries.

 Study the indexing methods like R-Tree, B-Tree, Bitmap for different queries.
 Scalability analysis for large datasets.

 4. Extensive evaluation of the performance of Sharded MongoDB cluster on range, spatial and search queries.
 5. Record the results and infer the limitations of the

Postgre SQL

MariaDB

systems based on the query latency.

Recommendations

1. Since data loading is periodical hence partial indexing must be supported in this framework to quickly add the new data to search index. 2. The framework must support

multiple indexing techniques at the same time, this is to make different types of queries work efficiently.

3. Indexing takes a lot of time hence a parallel hadoop job like implementation of building indexes on the distributed cluster is important and necessary.

4. The schema must be flexible to change the data model for different observations records, be it catalog, images, or normal spectral data.

Poster Credits: Samriddhi Jain



SCHOOL OF COMPUTING AND ELECTRICAL ENGINEERING INDIAN INSTITUTE OF TECHNOLOGY MANDI MANDI - 175005, INDIA

INTRODUCTION

Around the world we have lot of musical instruments but they can be broadly classified into four major groups, viz., Percussion, Plucking, String and Wind. The aim of the project is to classify the instrument not just according to the group but also, according to the instrument itself. The project comprises of mainly three steps:

- Preprocessing of data.
- Feature extraction.
- Classification using classifiers.

Monophonic sound of every instrument is being used. The aim of the project is also to analyze the effect that recording session variability plays in classification process.

DATASET

There are total 5 group of instruments (Flutes can be considered within wind instruments), with total of 16 instrument for our project as listed in Table 1.

Group	Instruments
Percussion	Drums, Mridangam, Tabla
Plucking	Guitar, Mandolin, Sitar, Veena, Banjo
String	Cello, Sarangi, Violin
Wind	Saxophone, Shehnai, Trumpet
Flutes	Bansuri, Western Flutes

Table 1: Groups and Instruments used in the Experiments

- Audio Files were collected from different sources on internet, a significant part of which came from YouTube. The audio files had sampling rate of 44.1 kHz.
- The audio files were segmented into 5s segments and cleaned manually using the steps shown in Diagram 1.



Diagram 1: Segmenting and Cleaning of Data

- To analyze the effects of session variability across different audio sources, four experiments were conducted:
- Training has seen Testing audio source
- a. Training and Testing come from same audio source (Diagram 2).
- Training using all sources and Testing from any audio source (Diagram 3).
- Training and Testing from different sources
 - Training from a single source (Diagram 4).
 - Training from multiple sources (70% for Training + 30% for Testing) (Diagram 5).

Classification of Musical Instruments from Audio

Sparsh Saurabh [B13334], Ritesh Kumar [B13133]; Mentors: Padmanabhan Rajan, Arnav Bhavsar





Diagram 2: Same Source for Train and Test

Diagram 3: Train using all Source

Diagram 4: Training using **Diagram 5:** Training using Single Source

For these experiments, dataset was divided once and this common dataset was used for conducting these experiments across different feature types and classification methods.

Apart from these four experiments, a dataset was also created for GMM-UBM, where 25% sources were used for UBM^[1], 25% sources for training and rest 50% sources were used for testing.

FEATURE EXTRACTION AND CLASSIFIERS

For feature extraction, four different methods were used:

- 1. Mel-frequency cepstral coefficients (MFCC)^[2]
- 2. MFCC with cepstral mean and variance normalization (CMV)^[3]
- 3. MFEC
- **4**. Chroma^[4]

For classification, three methods were used:

- Gaussian Mixture Model
- 2. Deep Neural Network
- GMM-UBM (Universal Background Model)

RESULTS

The result of experiments done for checking effects of session variability are shown below in Table 2.

Expt.	Experiments	MFCC		CMV		MFEC	CHROMA
No.		GMM	DNN	GMM	DNN	DNN	GMM
1.	Training and Testing from same	100.00%	99.07%	97.32%	94.67%	99.53%	93.13%
	source						
2.	Training using all sources	79.38%	95.59%	71.25%	87.538%	98.56%	85.63%
3.	Training from single source and	38.13%	37.73%	40.63%	46.90%	44.78	31.25%
	Testing from other source						
4.	Training using 70% of the sources	56.30 %	62.44%	61.96%	67.846%	74.07%	42.96%
	and Testing using rest 30%						
		• • •					

Table 2: Results for experiment to check effects of session variability

Results are shown for GMM with 10 mixtures in Table 2. Also, it must be noted that MFCC used in GMM was 39 dimensional while, in DNN, it was only 13 dimensional.







Multiple Sources

Following can be observed from Table 2:

- 46.9% and 74.07%.
- 3 and 4.

Few more experiments were performed with GMM-UBM (with mean-adaptation) and results for the same are shown in Table 3.

Expt. no.	Experiment	Source Distribution	MFCC	CMV	Chroma
	Single UBM for all				
1	classes	250/11 + 250/Tr + 500/To	53.96%	44.53%	31.46%
	Group Wise UBM	25% 0 + 25% 11 + 50% 10			
2	[see Table 1]		50.36%	47.66%	31.51%

Following can be observed from Table 3:

- GMM (with 70% sources for training and 30% for testing).
- training a simple GMM using 50% sources.

CONCLUSIONS

- important aspect of the project.
- **Experiment 3 and Experiment 4.**
- for classification of sounds.
- experiments were of the same order.

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• In Experiment 1 and Experiment 2, the highest accuracies are 100% and 98.56% respectively, while for Experiment 3 and Experiment 4, the highest accuracies were

• The better accuracies of Experiment 1 and 2 is because, in training step the recording environment of the testing files are already seen, which is not the case in Experiment

Thus, session variability is playing an important role in determining the accuracies.

Table 3: Results for GIVINI-UBINI [U: UBINI, Ir: Training, Ie: Testing]

Experiments for GMM-UBM have performed poorly as compared to experiments with

• This is mainly because, despite 25% sources being used for training UBM and then 25% being used for adapting UBM for each class, the process is not as effective as

The analysis of the effect of session variability on classification process is one of the

Both DNN and GMM have shown similar kind of behavior in all the experiments. In Experiment 1 and Experiment 2 both of them performed well in comparison to

No classification method or feature extraction method can give good performance until it is prone to session variability. Also, such a method can't be practically useful

• In the experiments conducted, DNN with MFEC features were the best performer, while GMM was next, and GMM-UBM was last. But, the results obtained in all these

Drone Video Analysis and Summarization An exploration of Bird's-eye view

Ashish Kumar Bedi & Samya Ranjan Patro Dr. Aditya Nigam & Dr. Arnav Bhavsar IIT Mandi | School of Computing and Electrical Engineering

Objectives and Challenges

In this project, we achieved the following two objectives, in drone video data:

- Multiple Object Annotation and Identification.
- Object Tracking.

We faced the following challenges while achieving the objectives:

- Object Re-identification.
- Zooming-in and out of the bounding box with moving object.

Data Collection

The data has been collected using DJI Phantom 3 Advanced Drone. The high resolution videos are captured at 40 fps. We collected this data by flying the drone inside and in surroundings of our Kamand campus. Figure 1 shows the type of data collected.

Data collection has been done such that the collected data included a variety of different objects, such as: buildings, pedestrians, playing ground, basketball and football.



Figure 1: Images of IIT Mandi, collected using DJI Phantom 3 Drone.

Object Annotation and Identification

State-of-the-art techniques have been implemented in YOLO v2 and SSD. Both of these are single shot detection techniques. We combined the output layers of the CNNs in YOLO v2 and SSD, and the corresponding results are better than those obtained from each of them individually. The area corresponding to the Jaccard Index of the outputs obtained from YOLO and SSD is being considered as the final output bounding box. Figure 2 shows the comparison between the architectures of the neural networks implemented in YOLO v2 and SSD.

Calculating accuracy: Let Jaccard Index of the output bounding box with the bounding box containing the actual object be J.

J > 0.85 implies *Correct Annotation* and J < 0.85 implies *Incorrect* Annotation.

Description	Number of Images
Images Tested	2000
Correctly Annotated as B2	852
Incorrectly Annotated as B2	40
Correctly Annotated as D2	912
Incorrectly Annotated as D2	24
Total Correctly Labelled	1692
Total Incorrectly Labelled	136
No Label	172
Accuracy	88.2%

Table 1: Results of the combination of YOLO v2 and SSD on our data-set.

SSD model adds several feature layers to the end of a base network, which predicts the offsets to default boxes of different scales and aspect ratios and their associated confidences. Below, we can see a comparison of the architectures of YOLO v2 and SSD:



Figure 2: Image showing the comparison between architectures of YOLO v2 and ssd



Figure 3: Image showing results of YOLO v2, SSD and combination of YOLO v2 and SSD on B2 Prashar Hostel, IIT Mandi. The red box corresponds to YOLO v2, blue to SSD and yellow to their combination.

Object Tracking

For object tracking in drone video, we have used state-of-the-art techniques implemented in STRUCK and MEEM

After modifying MEEM and STRUCK, we are now able to track objects in Bird's-eye view data. MEEM was performing slightly better, but it fails in certain scenarios, such as, in a video where background and foreground look similar in color. So, we incorporated the HOG, MBH and HAAR features of STRUCK into MEEM, to handle such cases. Modified MEEM gives better results as compared to MEEM, as can be seen in Table 2. These results show the average IoU of the output with the ground truth.



Both STRUCK and MEEM have a serious limitation, i.e., size of the bounding box is fixed. As the object moves towards the camera, size of the object increases as compared to the previous frames. Both the trackers fail to track the object in this case. We tackled this problem by computing the optical flow values, and training 3D Convolutional Neural Network on these values.



Figure 5: Left image depicts the optical flow between consecutive frame. Right image depicts the refined optical flow using first order derivatives.



Video No.	MEEM	Modified MEEM
1	0.65	0.68
2	0.71	0.75
3	0.53	0.58
4	0.55	0.63

Table 2: Results of MEEM and Modified MEEM tested on our Drone Video data.

Figure 4: Results of Meem and Modified Meem tested on Drone Video data.





Our model of 3D-CNN consists of two convolutional layers with 32 and 64 filters, one fully connected layer with 1024 neurons and one output layer predicting a single float value.

Conclusions

- STRUCK and MEEM.

Ongoing Research

- drone video.

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Figure 6: MEEM results after training on our 3D-CNN model

• We were able to improve the accuracy of the state-of-the-art neural networks, on the bird-view data. In order to achieve greater Accuracy for Object Annotation, we combined YOLO v2 and SSD and this worked with an accuracy of 88.2% on our data-set.

• We were able to solve the problem of Object Tracking, by studying and modifying the state-of-the-art techniques implemented in

• We were able to solve the task of dynamic bounding box sizes with change in Object's size in a video, by training 3D-CNN on optical flow values, computed between two consecutive frames.

• We tackled the problem of Object Identification and Annotation using YOLO. But, YOLO provides only spatial understanding of the object. In order to get both spatial and temporal understanding, we are modifying and training ROLO on our drone video data-set. ROLO is an LSTM layer applied over YOLO. We are modifying ROLO to also tackle the problem of Object Re-identification in a

• Improving accuracy of our 3D-CNN model by evaluating the values of hyper-parameters which work best on the 3D data.

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Opening Lead Recommendation in Contract Bridge



Gopal Krishan Aggarwal & Naman Gupta

Prof. Deepak Khemani

School of Computing and Electrical Engineering (SCEE), IIT Mandi, Himachal Pradesh, India



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- Other classification algorithms such as
 - Random Forest were also tried.



Line Fault Detection in Tennis and Video Summarization Rohit Bishnoi(B13134) Mentor: Dr. Renu M. Rameshan and Dr. Aditya Nigam

Problem Statement

Results

Detecting line fault and video summarization in tennis without Results without using Kalman Filter are not acceptable because the amount of error in the measured value leads to a large human input. This project uses 3D tracking to solve this amount of error projected 3D location of the ball.

ground are some challenges faced during project.

problem. This technique will only work on data recorded with Kalman Filter results are not that good. One reason for this is modeling. Kalman Filter model require some more changes two calibrated cameras. Speed of ball, exact spot of the ball on for specific cases. Other reason is the unsynchronized data. Data captured using two cameras was not properly synchronized which leads to error in results.





A setup of two camera is used in this project which are placed The point where ball touches the ground, the velocity of ball changes due to non-elastic collision. This special case is added at certain distance and then calibrated. Each pair of camera in Kalman Filter using control input model. This control input model only effects the Kalman Filter for the point where ball covers both lines in corner. So for whole ground four such touches the ground. Controlled input consider the collision to be inelastic and uses coefficient of restitution for calculating pair will be needed. velocity after the impact.



0.0037 0.9886 -0.1507 -0.0170 0.1508 0.9884



The improvement in result after using controlled input model is significant. But still Kalman Filter requires more effective model to track with precision. Translation vector: T = [148.39276 -1.55872 -6.53204]mm



Technique used in this project requires images from both the

The ball in image(2D) is tracked using STRUCK. STRUCK is a tracking-by-detection technique. STRUCK is applied on frames by left camera. Then using result by STRUCK, NCC is used to calculated position of ball(2D) in right image and depth of the ball.



When the ball goes out of frame then YOLO is used to detect the ball when it comes back. YOLO is also used when STRUCK tracking fails





STRUCK and Kalman Filter performance was better when they were used parallel rather then using sequentially. Reason

included all lines in ground. Then horizontal lines and very small vertical lines are ignored. After this overlapping lines are merged into line to detect the required line tennis field.





3D Tracking

Then using all theses results are provided to Kalman Filter to track the ball in real world co-ordinate(3D). Kalman Filter is a algorithm which based on series of measurements, estimates unknown variable. Due to non-linear transformation matrix in Kalman Filter Extended Kalman Filter is used.

Conclusion		
$R = E[v_t v_t^T]$		$I_{t t} = (I - K_t \cdot H) \cdot I_{t t-1}$
$Q = E[w_t w_t^T]$		$P_{i} = (I - K_{i}H) \cdot P_{i}$
F is the model	$P_{t t-1} = F \cdot P_{t-1 t-1} \cdot F + Q$	$K_t = P_{t \mid t-1} \cdot H^T \cdot (H \cdot P_{t \mid t-1} \cdot H^T + R)^{-1}$
H is transformation matrix	$P = F \cdot P \cdot F^T + O$	$z_e = H \cdot U_{t \mid t-1} + v_t$
$P_{t t-1} = E\left[\left(U_t - U_{t t-1}\right) \cdot \left(U_t - U_{t t-1}\right)^T\right] \text{ Convariance Matrix}$	$U_{t t-1} = F \cdot U_{t-1 t-1} + W_t$	
$z = [x1 \ y1 \ x2 \ y2 \ Z]^T$ Measurments		$U_{\text{the}} = U_{\text{the}} + K_{\text{the}} (z - z_{\text{the}})$
$U = \begin{bmatrix} X & Y & Z & \dot{X} & \dot{Y} & \dot{Z} & \ddot{X} & \dot{Y} & \ddot{Z} \end{bmatrix}^{t} State Variable$	Prediction Step	Update Step

Modeling of Kalman Filter is a step by step process.Once all these steps are covered then it is expected that even if STRUCK fails at some point Kalman Filter will not so tracker will eventually work good. We tried to cover most of the cases and correct most of the reasons for error but still the Kalman Filter is not working as expected. With Kalman Filter not working properly it is hard to predict the exact spot on which the ball touches the ground and without that the B(control-input model) would not work. So these points are provided manually.



1160

100 1160 1170 1180 1190 1200 1210 1220 1230 1240 1170 1180 1190 1200 1210 1220 1230 1240

for this STRUCK can use the predicted values of Kalman Filter and use it to track ball in next frame. After tracking the ball lines in tennis ground is detected using Hough and Canny. Initial result given by Hough and Canny





Quantum Maxflow Mincut Problem

Under the guidance of Dr. Samar Agnihotri

About the Project:

In a graph, the maximum flow is equal to the bottleneck capacity of the network.
It takes quadratic runtime to calculate minimum capacity by the best known algorithm.
Our aim is to improve this runtime using Quantum Computation.



a typical rail network



Existing Algorithm:

Best known algorithm given by Stoer and Wagner QUANTUM MAX-FLOW/MIN-CUT gives a time complexity of:

 $O(|V||E| + V^2 \log |V|)$

 $\begin{array}{c} -2 & -3 \\ -2 & -2 & 0 \\ -2 & -3 \end{array}$

A tensor network

A classical network

In case of large networks, where V and E are huge, time complexity almost becomes cubic.

The Proposed Algorithm:

To calculate mincut in a graph, the problem is divided into 2 parts: **Classical part:** it enumerates all the cutsets in a graph using quadratic time. **Quantum part:** It calculates the minimum among them by implementing a quantum algorithm built upon Grover's search algorithm in squared root run time.

Classical part

We first enumerate all cutsents using the classical algorithm given Tsukiyama and Shirakawa. Its time complexity is:

 $O((|V| + |E|)(|V| - \log r)r)$

Now apply quantum part to evaluate min of these using sqaured root complexity.

Result

Quantum part

Built upon Grover's algorithm:
1. Choose a value p from the set of cuts enumerated by the classical part.
2. Repeat:

i. Apply Grover's algorithm and find q such thatq<p.
ii. If we find such a q, reset p as q. Else, output p as result.



Speedup is achieved in the calcualtion of mincut from almost cubic time to quadratic (in the classical part) and squared root in the quantum part.

Setting up of WRF-GFS Model for Regional Climate Prediction Abhimanyu Mittal

Under the guidance of Dr. Sarita Azad

OBJECTIVE

•To obtain the high resolution numerical prediction of precipitation over the Indian region using Weather Research and Forecasting (WRF) System

•Examining the 6-hour global forecast output may not give a satisfactory picture of the likely forecast uncertainty on the local scale. This poster describes a system that uses the (WRF) model to effectively downscale the GFS members over a small region.



METHODOLOGY AND DATA

Use of Advanced Research WRF (ARW) core of the Weather Research and Forecasting System (WRF)
6h Global Forecasting System (GFS) at 1.0 X 1.0° grids generated by NCEP's global forecast system.
May 15, 2017 0000 hrs to May 23, 2017 0600 hrs



WRF Workflow

WRF Domain and Configuration



Manages execution over nested grids
 Controls input/output
 Top-level control over parallel processing

- Makes calls to parallel mechanisms

- Contains numerics and physics - Performs model computations

WRF Model Architecture

•ARW Version: 3.4.1

•Long-Wave Radiation Scheme: RRTM

Short-Wave Radiation Scheme: Dudhia

•Surface Clay Physics: Monin-Obukhov similarity theory •Surface Physics: 5 layer thermal diffusion model from MM5 •PBL Scheme: YSU

•MP Physics: WSM3

Forecast Product



WRF Precipitation Simulations for Delhi



WRF Precipitation Simulations for Bangalore

RESULTS

•The likely default configurations using the GFS domain gives more or less the same result for all the planar areas

- •The ~10 km spatial resolution simulation could be made in approx 2-3 mins while the ~3 km spatial resolution took about 24-25 mins per location.
- •Forecasting of precipitation and surface temperature for the local Himachal Pradesh region was tried but the main challenge attached with it is the drastically changing terrain height. To counter this problem, the WRF-IBM module is needed with the alternative parameterization methods to obtain real forecasting results.

FUTURE WORK

- Assimilation of satellite observations of the atmosphere to improve skill in precipitation forecasts
- •Evaluation and Verification of model performance using forecasted boundary data from NWP models other than NOAA models
- Exploring further refinements to the proposed default set of parameterization configuration

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Streaming Based Genome Mapping on Apache Flink Ankush Jindal, Sagar Ghai Under the guidance of Dr. Arti Kashyap

INTRODUCTION

- Genome Sequencing is process of determining the complete DNA sequence of an organism's genome.
- Genome Mapping is aligning the reads (small sequence of base pairs) onto a reference genome.





Apache Flink's Core Programming Model

DATASETS

Apache Flink

Dataset	Size (in MB)	AVLR-Spark	Spark BWA	AVLR-Flink
chr1	254	105	301	1080
chr2	248	90	254	958
chr3	201	81	203	1843
chr5	184	72	183	867
hg19	3157	774	3274	-

RESULTS : AVLR-Flink vs Others



Index Generation time for AVLR-Spark, Spark BWA, AVLR-Flink

CONCLUSION

- Spark clearly outperforms Flink in doing the sequence alignment by AVLR-Mapper
- AVLR-Flink's results were accurate both for batch processing and streaming data
- The streaming based sequence alignment tool will take almost 'zero' additional time for mapping when the mapper is run in parallel to the sequencer using streaming capabilities. Even though Spark outperforms Flink's implementation of AVLR-Mapper in index generation, it will take smaller net time in the mapping of the reads.

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OBJECTIVE

- Challenge: Reduce the read-mapping time
- **Objective**: Develop the flow for streaming manner read mapping, while implementing AVLR-Mapper (sequencing and mapping) in Apache Flink (both for streaming data and batch processing) and compare results with current state of the art.



Agilent's Sequencing and Mapping Workflow

AVLR-Mapper Algorithm



Iteration 1: Suffix Generation

Read Data	Offset, Read		Combine Results	Read Results
Read1 Read2		MAP-1 RG Index		Read1, 57, 5 Read2, 31, 3
Read3	1, R1 8, R2		Read2, 31, 33	Read3, 33, 3 Read4, 12, 1
Read5	<u></u>	MAP-2 RG Index	\longrightarrow	Read5, 14,
Read6 Read7	22, R4 29, R5		Read4, 12, 14 Read5, 14, 16	Read6, 20, 2 Read7, 22, 2
Read8 Read9	42. D7	MAP-3 RG Index	Deads 34 36	Read8, 34, 3 Read9, 40, 4
Read10	43, K7 50, R8		Read9, 40, 42	Read10. 46.

Iteration 2: Mapping

WIRELESS POWER TRANSFER 2.0

Shri Kisna Mahajan B13230

Munindar Kumar B13216

Avanish Yadav B13205

School of Computing and Electrical Engineering , Indian Institute of Technology



OBJECTIVES

- · To develop a design for the secondary coil to decrease sensitivity of the setup because of misalignment of primary and secondary coils.
- Develop a theoretical model of the multidimensional secondary coil setup.
- Experimentally validate the theoretical model.
- Design a rectifier circuit to provide a DC voltage as output from the set of secondary coils.























































Contact Us:

If you have any queries, then mail us at

chairscee@iitmandi.ac.in

sceeoffice@iitmandi.ac.in

Contact Number: +91-1905-267133

+91-1905-267046