Exemplar based approaches on faces

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by

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CERTIFICATE

It is certified that the work contained in this thesis, titled "Exemplar based approaches for faces" by Mallikarjun B R, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date	Adviser: Prof. C V Jawahar

To My Family

Acknowledgments

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Abstract

Multiplying two sparse matrices, denoted spmm, is a fundamental operation in linear algebra with several applications. Hence, efficient and scalable implementation of spmm has been a topic of immense research. Recent efforts are aimed at implementations on GPUs, multicore architectures, FPGAs, and such emerging computational platforms. Owing to the highly irregular nature of spmm, it is observed that GPUs and CPUs can offer comparable performance (Lee et al. [39]).

In this paper, we study CPU+GPU heterogeneous algorithms for spmm where the matrices exhibit a scale-free nature. Focusing on such matrices, we propose an algorithm that multiplies two sparse matrices exhibiting scale-free nature on a CPU+GPU heterogeneous platform.

Our experiments on a wide variety of real-world matrices from standard datasets show an average of 25% improvement over the best possible algorithm on a CPU+GPU heterogeneous platform. We show that our approach is both architecture-aware, and workload-aware.

The architectural trend towards heterogeneity has pushed heterogeneous computing to the fore of parallel computing research. Heterogeneous algorithms, often carefully handcrafted, are designed for several important problems from parallel computing such as sorting, graph algorithms, matrix computations, and the like. A majority of these algorithms follow a work partitioning approach where the input is divided into appropriate sized parts so that individual devices can process the right parts of the input. Such a division is done by means of thresholds. However, identifying the right value of the threshold is usually non-trivial and may require extensive empirical search. Such an extensive empirical search may potentially offset any gains accrued out of heterogeneous algorithms.

In this paper, we propose a simple and effective technique to identify the required thresholds in heterogeneous algorithms. Our technique is based on sampling and therefore can adapt to the algorithm used and the input instance. Our technique is generic in its applicability as we will demonstrate in this paper.

We validate our technique on two problems: finding the connected components of a graph and multiplying two scale-free sparse matrices. For these two problems, we show that using our method, we can find the required threshold that is $\pm$ 5% and $\pm$ 7.5% away from the best possible threshold, respectively. Along the way, we design a novel heterogeneous algorithm for sparse matrix multiplication when the matrices are scale-free in nature. This algorithm outperforms the existing best known algorithms for sparse matrix multiplication by 22% on average on a wide variety of matrices drawn from standard datasets.

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Chapter 2

Fiducial detection

2.1 Abstract

Facial fiducial detection is a challenging problem for several reasons like varying pose, appearance, expression, partial occlusion and others. In the past, several approaches like mixture of trees [**?**], regression based methods [**?**], exemplar based methods [**?**] have been proposed to tackle this challenge.

In this paper, we propose an exemplar based approach to select the best solution from among outputs of regression and mixture of trees based algorithms (which we call candidate algorithms). We show that by using a very simple SIFT and HOG based descriptor, it is possible to identify the most accurate fiducial outputs from a set of results produced by candidate algorithms on any given test image. Our approach manifests as two algorithms, one based on optimizing an objective function with quadratic terms and the other based on simple kNN. Both algorithms take as input fiducial locations produced by running state-of-the-art candidate algorithms on an input image, and output accurate fiducials using a set of automatically selected exemplar images with annotations. Our surprising result is that in this case, a simple algorithm like kNN is able to take advantage of the seemingly huge complementarity of these candidate algorithms, better than optimization based algorithms.

We do extensive experiments on several datasets, and show that our approach outperforms state-of-the-art consistently. In some cases, we report as much as a 10% improvement in accuracy. We also extensively analyze each component of our approach, to illustrate its efficacy.

An implementation and extended technical report of our approach is available www.sites.google.com/site/wacv2016face

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Related Publications

- *Kiran Raj Ramamoorthy, Dip Sankar Banerjee, Kannan Srinathan and Kishore Kothapalli,* A Novel Heterogeneous Algorithm for Multiplying Scale-Free Sparse Matrices, **IEEE - IPDPS, ASHES 2015**.
- *[Submitted] Hardhik Mallipeddi, Kiran Raj Ramamoorthy and Kishore Kothapalli,* Nearly Balanced Work Partitioning via Sampling for Heterogeneous Algorithms, **IEEE - 2016** .

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