October 1989

NAG1-613

UILU-ENG-89-2235
CSG-112

COORDINATED SCIENCE LABORATORY
College of Engineering

285.

PARALLEL IMPLEMENTATION AND EVALUATION OF MOTION ESTIMATION SYSTEM ALGORITHMS ON A DISTRIBUTED MEMORY MULTIPROCESSOR USING KNOWLEDGE BASED MAPPINGS

Alok N. Choudhary
Mun K. Leung
Thomas S. Huang
Janak H. Patel

UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION Unclassified	1b. RESTRICTIVE MARKINGS None
2a. SECURITY CLASSIFICATION AUTHORITY	3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution unlimited
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE	
4. PERFORMING ORGANIZATION REPORT NUMBER(S) UILU-ENG-89-2235 (CSG-112)	5. MONITORING ORGANIZATION REPORT NUMBER(S)
6a. NAME OF PERFORMING ORGANIZATION Coordinated Science Lab University of Illinois 6b. OFFICE SYMBOL (If applicable) N/A	7a. NAME OF MONITORING ORGANIZATION NASA / NSF
6c. ADDRESS (City, State, and ZIP Code) 1101 W. Springfield Avenue Urbana, IL 61801	7b. ADDRESS (City, State, and ZIP Code) NASA Langley Research Center Hampton, VA 23665 National Science Foundation 1800 G Street, NW / Washington DC 20550
8a. NAME OF FUNDING/SPONSORING ORGANIZATION NASA / NSF 8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER NASA NAG 1-613 NSF IRI 87-05400
8c. ADDRESS (City, State, and ZIP Code) see 7b	10. SOURCE OF FUNDING NUMBERS PROGRAM ELEMENT NO. / PROJECT NO. / TASK NO. / WORK UNIT ACCESSION NO.

11. TITLE (Include Security Classification)
Parallel Implementation and Evaluation of Motion Estimation System Algorithms on a Distributed Memory Multiprocessor using Knowledge Based Mappings

12. PERSONAL AUTHOR(S)
Alok N. Choudhary, Mun K. Leung, Thomas S. Huang and Janak H. Patel

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
Technical	FROM _____ TO _____	89/10	25

16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	computer vision, motion estimation, motion estimation system algorithms

19. ABSTRACT (Continue on reverse if necessary and identify by block number)
Computer vision systems employ a sequence of image understanding vision algorithms in which the output of an algorithm is the input of the next algorithm in the sequence. Vision systems consist of algorithms that exhibit varying characteristics, and therefore, require different data decomposition and efficient load balancing techniques for parallel implementation. However, since the input data of a task is produced as the output data of the previous task, this information can be exploited to perform knowledge based data decomposition and load balancing. This paper presents several techniques to perform static and dynamic load balancing techniques for vision systems. These techniques are novel in the sense that they capture the computational requirements of a task by examining the data when it is produced. Furthermore, they can be applied to many vision systems because many algorithms in different systems are either same, or have similar computational characteristics. These techniques are evaluated by applying them on a parallel implementation of the algorithms in a motion estimation system on a hypercube multiprocessor system. The motion estimation system consists of the following steps: 1) extraction of features, 2) stereo match of images in one time instant, 3) time match of images from different time instants, 4) stereo match to compute final unambiguous points and, 5) computation of motion parameters. It is shown that the performance gains when these data decomposition and load balancing techniques are used are significant and the overhead of using these techniques is minimal.

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT. ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION Unclassified
22a. NAME OF RESPONSIBLE INDIVIDUAL	22b. TELEPHONE (Include Area Code) / 22c. OFFICE SYMBOL

Parallel Implementation and Evaluation of Motion Estimation System Algorithms on a Distributed Memory Multiprocessor using Knowledge Based Mappings

Alok N. Choudhary, Mun K. Leung, Thomas S. Huang and Janak H. Patel

Coordinated Science Laboratory
University of Illinois
1101 W. Springfield
Urbana, IL 61801

Address for Correspondence

Corresponding Author : Alok N. Choudhary
Department of Electrical and Computer Engineering
Science and Technology Center
Syracuse University
Syracuse, NY 13244

Mun K. Leung, Thomas S. Huang and Janak H. Patel
Coordinated Science Laboratory
University of Illinois
1101 W. Springfield
Urbana, IL 61801

Conference : Computer Architectures Vision and Pattern Recognition

Neither this paper nor any version close to it has been or is being offered for publication elsewhere. If accepted, the paper will be personally presented at the designated 10ICPR by the author or one of the co-authors.

Alok N. Choudhary

Parallel Implementation and Evaluation of Motion Estimation System Algorithms on a Distributed Memory Multiprocessor using Knowledge Based Mappings

Alok N. Choudhary, Mun K. Leung, Thomas S. Huang and Janak H. Patel

Coordinated Science Laboratory
University of Illinois
1101 W. Springfield
Urbana, IL 61801

Abstract

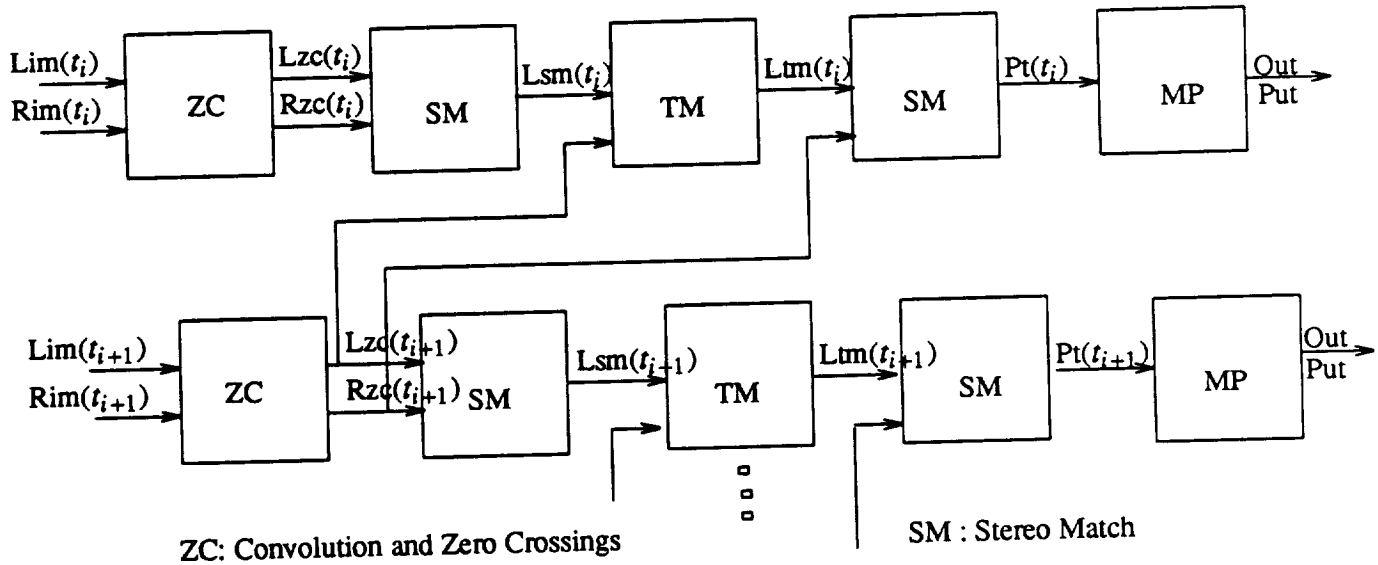
Computer vision systems employ a sequence of image understanding vision algorithms in which the output of an algorithm is the input of the next algorithm in the sequence. Vision systems consist of algorithms that exhibit varying characteristics, and therefore, require different data decomposition and efficient load balancing techniques for parallel implementation. However, since the input data of a task is produced as the output data of the previous task, this information can be exploited to perform knowledge based data decomposition and load balancing. This paper presents several techniques to perform static and dynamic load balancing techniques for vision systems. These techniques are novel in the sense that they capture the computational requirements of a task by examining the data when it is produced. Furthermore, they can be applied to many vision systems because many algorithms in different systems are either same, or have similar computational characteristics. These techniques are evaluated by applying them on a parallel implementation of the algorithms in a motion estimation system on a hypercube multiprocessor system. The motion estimation system consists of the following steps: 1) extraction of features, 2) stereo match of images in one time instant, 3) time match of images from different time instants, 4) stereo match to compute final unambiguous points and, 5) computation of motion parameters. It is shown that the performance gains when these data decomposition and load balancing techniques are used are significant and the overhead of using these techniques is minimal.

This research was supported in part by National Aeronautics and Space Administration Under Contract NASA NAG-1-613, and in part by National Science Foundation Grant IRI 87-05400.

1. Introduction

Computer vision tasks employ a broad range of algorithms. In vision system many algorithms with different characteristics and computational requirements are used in a sequence where output of one algorithm becomes the input of the next algorithm in the sequence [1,2]. An example of such a system is a motion estimation systems. In such a system, a sequence of images of a scene are used to compute the motion parameters of a moving object in the scene. Figure 1 shows the computational flow for a motion estimation system in which stereo images (L_{im} and R_{im}) at each time frame are used as the input to the system. Briefly, the involved tasks (or algorithms) in this system are as follows. The first algorithm is computation of zero crossings of the images (edge detection (L_{zc} and R_{zc})). The zero crossings are used as feature points for both stereo and time matching. The stereo match algorithm provides points to compute 3-D information about the object in the scene. Using these matched points (Lsm and Rsm), the corresponding points in the image in the next time frame (L_{tm}) are located and this task is performed by time match algorithm. Again, stereo match is used to obtain the corresponding 3-D points in the next image frame. These two sets of points provide information to compute the motion parameters. The above process is repeated for each new set of input image frame.

This paper presents techniques to perform efficient data decomposition and load balancing for vision systems for medium to large grain parallelism. Two important characteristics of these techniques are that they are general enough to apply to many vision systems, and that they use statistics and knowledge from execution of a task to



ZC: Convolution and Zero Crossings SM : Stereo Match

TM: Time Match MP: Motion Parameter Computation

Figure 1 : Computation Flow for Motion Estimation

perform data decomposition and load balancing for the next task. For example, in the motion estimation system sufficient knowledge can be obtained about the output data from the zero crossing step to perform data decomposition and load balancing for the stereo matching step. The advantages of such schemes are as follows. First, these techniques use characteristics of tasks and data, and therefore, work well no matter how data changes. Second, many vision systems consist of such tasks and exhibit the above described computation flow, and therefore, these techniques can be used in any system (e.g., object recognition, optical flow etc.) [2].

The performance of the proposed techniques is evaluated by using a parallel implementation of the motion estimation system algorithms on a hypercube multiprocessor system. The results show that using uniform partitioning, without considering the computations involved, parallel processing does not provide significant performance improvements over sequential processing. Furthermore, by applying the proposed data decomposition and load balancing techniques significant performance gains (as much as 6 fold) can be obtained over uniform partitioning.

This paper is organized as follows. In Section 2 we provide a brief description of each step in the motion estimation system . For a detailed description, the reader is referred to [3,4]. These algorithms will provide insight into the involved computations in the motion estimation system. Section 3 describes the proposed load balancing and data decomposition techniques. In section 4 we present a parallel implementation of these algorithms in an integrated environment on a hypercube multiprocessor, and discuss the performance results for each of these algorithms and data decomposition and load balancing schemes. Some of these techniques have been applied to other integrated vision systems and have been shown to work well [2, 5]. Finally, concluding remarks are presented.

2. Steps in the Motion Estimation System

The motion estimation system consists of the following steps: 1) extraction of features, 2) stereo match of images in one time instant, 3) time match of images from different time instants, 4) stereo match to compute final unambiguous points and, 5) computation of motion parameters. We will not discuss, the last process, calculation of motion parameters, but a discussion on how to compute them can be found in [6]. The matching algorithms use stereo image pairs, and the algorithms are designed to find point correspondences between two consecutive time instants, i.e., t_{i-1} and t_i. From the point correspondences, we can estimate the motion parameters. Typical stereo image pairs at two consecutive time instants (t_7 and t_8) used in this paper are shown in Figure 2, which are outdoor scenes of truck at different locations. The images are segment out from larger images of size 1024×1024. The imaging setup used in taking the images is parallel axis method. The feature points used in the matching process are

edge points which are considered as the more reliable features obtained from an image. In order to save considerable computation time, the matching process in done by employing non-iterative procedures with the assumption of limited displacement (or disparity) between frames. We apply the matching algorithm on two stereo image pairs at two consecutive time instants t_7 and t_8. The following is a brief description for each major step of the motion estimation system.

2.1. Feature Points

The feature points used in this algorithm are zero crossing points of an image. We use the method suggested by Huertas and Medioni in [7] to extract the zero crossings of an image. In order to eliminate non-significant zero crossing points and maintain enough details, we threshold the zero crossing image based on the intensity gradient at each zero crossing point. Figure 3 depicts one of the thresholded zero crossing images, l_7. We associate each zero crossing point with one the sixteen possible zero crossing patterns as suggested and used by Kim and Aggarwal [8]. The patterns are not used directly; instead, we assign each pattern a value according to its local connectivity. These pattern values are used in the matching process.

2.2. Matching

Once zero crossings are extracted in all the involved images, the matching process is applied to find point correspondences among the images (two stereo image pairs at two consecutive time instants). The evidences used in this process to obtain matched point pairs are the normalized correlation coefficient, and the zero crossing pattern values. Furthermore, in order to limit the search space, the assumption of limited displacement or disparity between frames is exploited. The matching process consists of six steps as follows:

1) Perform stereo (from left to right) matching in the t_{i-1} stereo image pair.

2) Obtain unambiguous matched point pairs by eliminating multiple matches.

3) Perform time matching between the unambiguous matched points in the left t_{i-1} image and the feature points of the left t_i image.

4) Obtain unambiguous matched point pairs from the time matched points by eliminating multiple time matches.

5) Perform stereo matching between the unambiguous matched points (obtained in step (4)) in the left t_i image and the feature points of the right t_i image.

6) Obtain unambiguous matched point pairs from the results of t_i stereo matching by eliminating multiple matches.

The results of the above steps are two sets of unambiguous stereo matched point pairs at time instant t_{i-1} and t_i. These two sets are related through steps (3) and (4), the matching over time; therefore, we can pick out all the unambiguous matched points that correspond to each other among the two stereo image pairs at time instants t_{i-1} and t_i. The matching algorithm was applied to the images shown in Figure 2. The final results are depicted in Figure 4, which shows that we have enough point correspondences for the motion estimation.

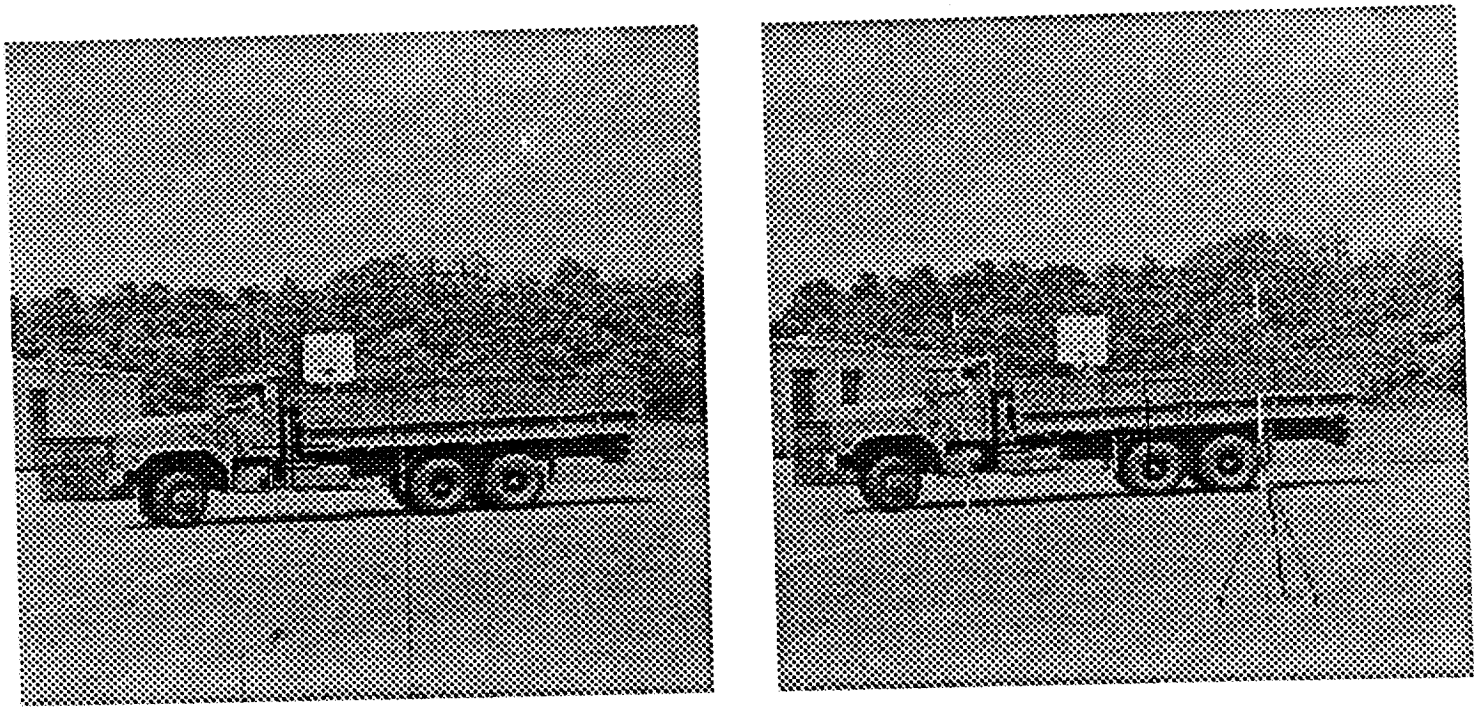
3. Data Decomposition and Load Balancing Techniques for Parallel Implementation

In a multiprocessor system the simplest method to implement a task in parallel is to decompose the data and equally and uniformly among the processors. In a completely deterministic computation in which the computation is independent of the input data such schemes perform well, and normally, the processing time is comparable on all the processors. That is, efficient utilization and load balancing can be obtained. For example, regular algorithms such as convolutions, filtering or FFT exhibit such properties. The amount of computation to obtain each output point is the same across all input data. Therefore, uniform decomposition of data results in load balanced implementation.

Most other algorithms do not exhibit a regular structure, and the involved computation is normally data dependent. Furthermore, the computation is not uniformly distributed across the input domain. In such cases, a simple decomposition of data does not provide efficient mapping, and results in poor utilization and low speedups. Also, the performance cannot be predicted for a given number of processors, and a given data size, because the computation varies as type of data and its distribution varies. For example, in the stereo match algorithm, the computation is more where feature points are dense, and is comparatively small where number of features is small and sparsely distributed (Figure 3).

In a vision system, it is important to efficiently allocate resources and perform load balancing at each step to obtain any significant performance gains overall. An important characteristic of such systems is that the input data of a task is the output of the previous task. Therefore, while computing the output in the previous task enough

(a) Left and right images at time instant t_7



(b) Left and right images at time instant t_8
Figure 2 : Images set of t_7 and t_8

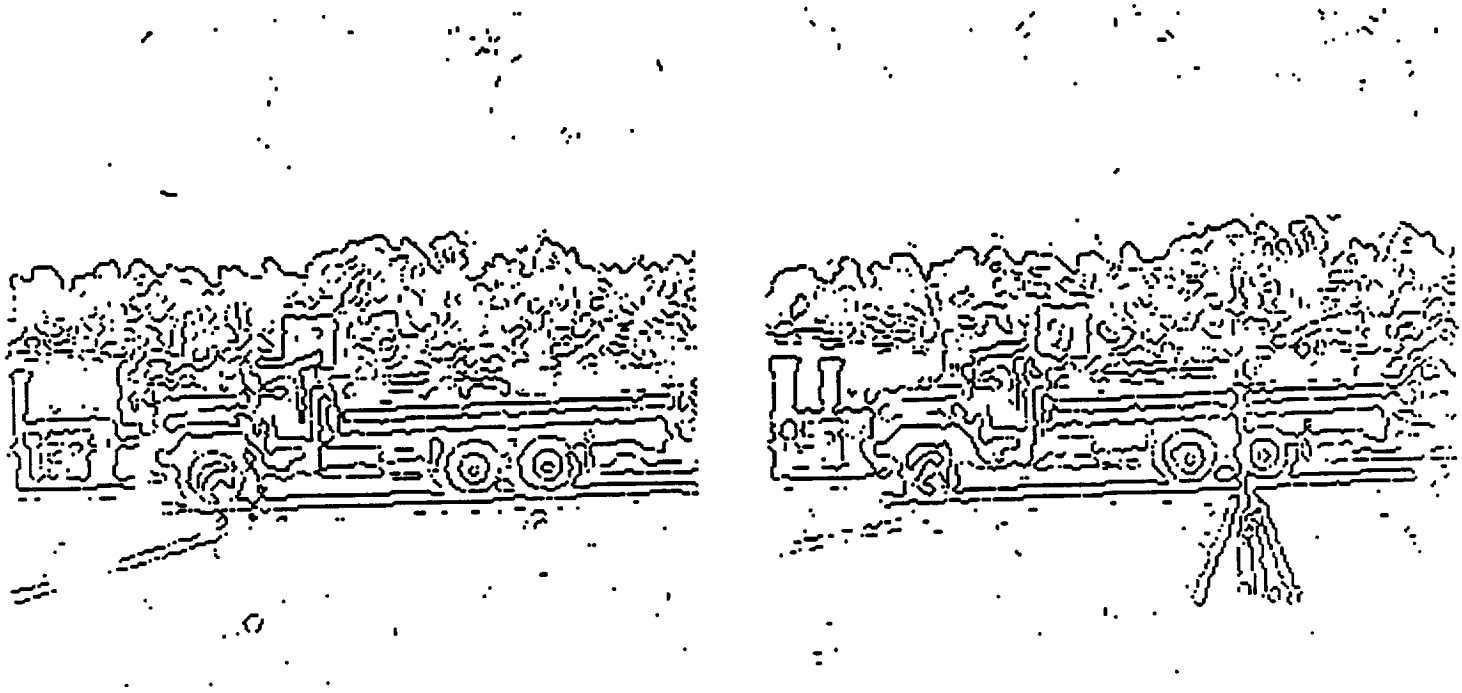
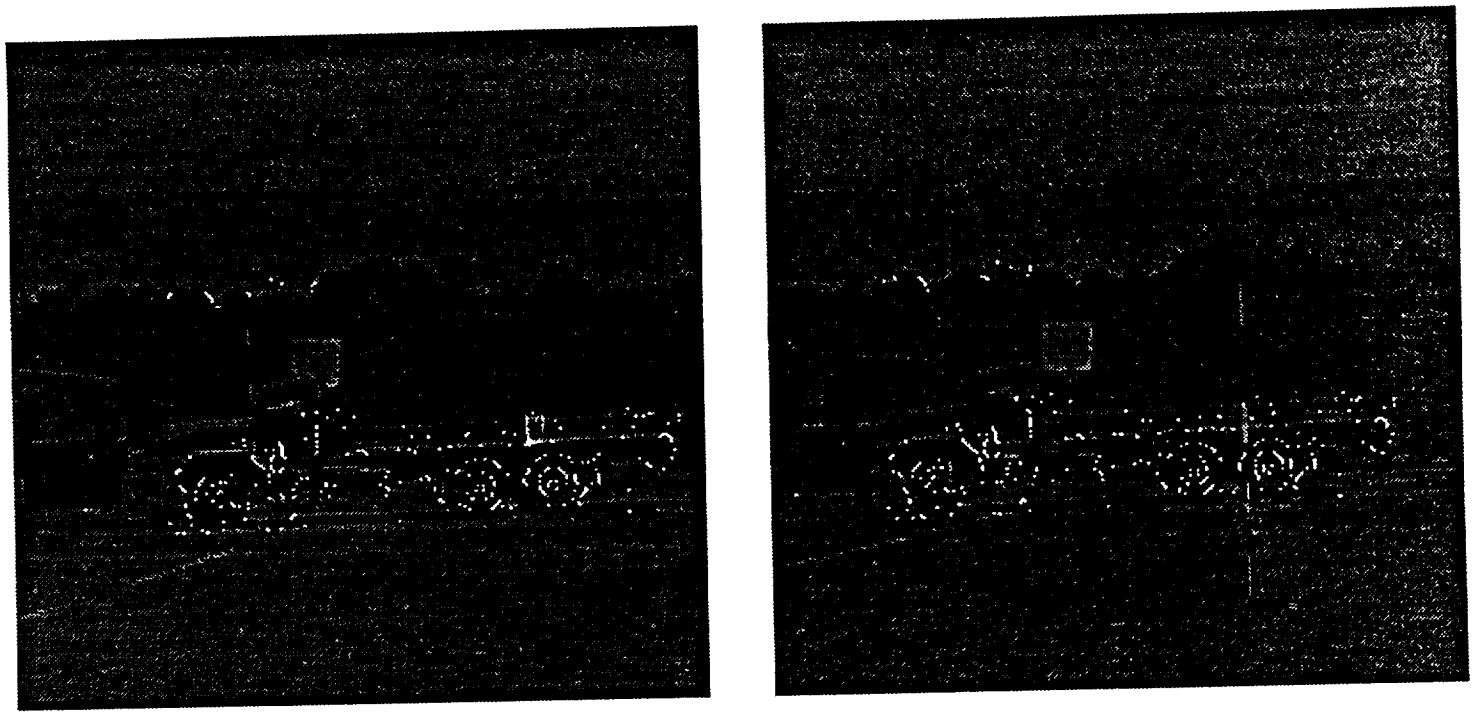
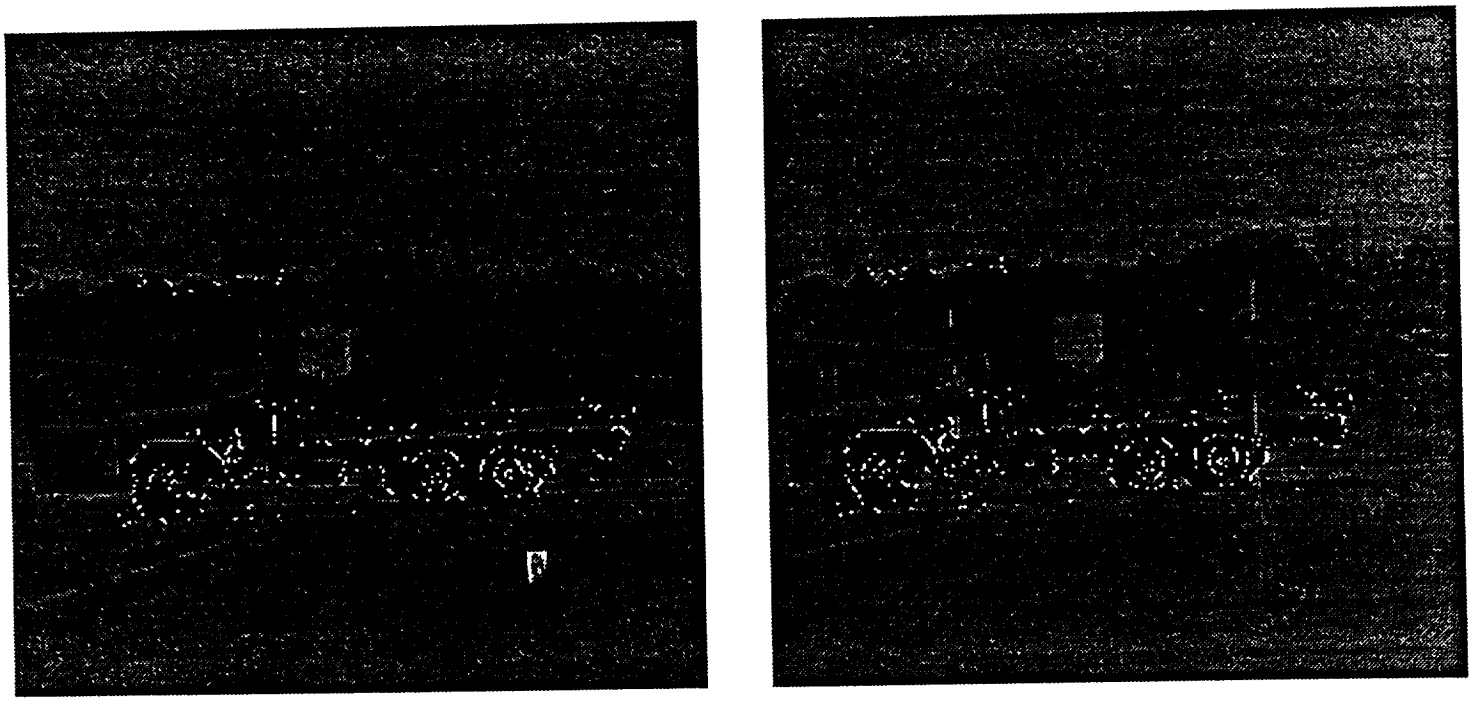


Figure 3 : Left and right zero crossings at time instant t_7



(a) : At time instant t_7



(a) : At time instant t_8

Figure 4 : Unambiguous matched points of Figure 2

knowledge about the data can be obtained to perform efficient scheduling and load balancing.

Consider a parallel implementation of a task on n processor parallel machine. Let T_i $(1 \le i \le n)$ denote the computation time at processor node i. Then the overall computation time for the task is given by

$$T_{\max} = \max\{T_1, \ldots, T_n\} \tag{1}$$

The total wasted time (or idle time) T_w is given by

$$T_w = \sum_{i=1}^{i=n} (T_{\max} - T_i) \tag{2}$$

If $T_{\max} = T_i$ for all i, $1 \le i \le n$, then the task will be completely load balanced. Another measure of imbalance is given by the variation ratio V,

$$V = \frac{T_{\max}}{T_{\min}}, \quad T_{\min} = \min\{T_1, \ldots, T_n\} \tag{3}$$

The goal in performing load balancing is to minimize T_w, or move V as close to 1 as possible. In the best case, $T_w = 0$ or $V = 1$.

If T_{seq} is the time to execute the same task on a sequential machine then the speedup is given by

$$S_p = \frac{T_{seq}}{T_{\max}} \tag{4}$$

Therefore, by minimizing T_w, the achievable speedup can be maximized. In the following we discuss such techniques, and in the next section we present the performance results for a parallel implementation of algorithms in the motion estimation system.

3.1.1. Uniform Partitioning

Data decomposition using uniform partitioning performs well as a load balancing strategy for input data independent tasks, because equally dividing the data distributes the computation equally among processors. If total input data size is D then total computation time to execute a task is $T = k \times D$, where k is determined by the computation at each input data point. For example, in convolution of an image with $m \times m$ kernel, $k = 2 \times m^2$ floating point operations. Hence, for an n node multiprocessor, the data decomposition methods to balance the computation is to make the granule size to

$$d_i = \frac{D}{n} \tag{5}$$

For data independent algorithms, such a partitioning guarantees equal distribution of computation among processors. Therefore, if communication time can be minimized, then optimal performance can be obtained on a given multiprocessor.

3.1.2. Static

When computation is not uniformly distributed across the input domain, and is data dependent, uniform partitioning does not work well for load balancing. Normally, computation depends on significant data elements in a partition. Many vision algorithms exhibit this behavior. For example, in stereo match, hough transform etc., the computation is proportional to the number of features (edges) or significant pixels in a granule rather than on the granule size. Therefore, equal size granules do not guarantee load balanced partitioning because of the data dependent nature of the computation. In many such algorithms, the computation time for a granule (i), T_i, is proportional to a certain extent on the granule size (fixed overhead to process a granule), and to the number of significant data in a granule. That is,

$$T_i = A \times d_i + B \times f_i \tag{6}$$

where, d_i is the granule size, f_i is a measure of significant data in granule (i), and A and B are arbitrary constants which depend on the algorithm. The objective is to divide the computation among processors such that each processor receives equal measure of computation. One way to assign a granule to a processor is to compute the total measure of computation and partition is as follows:

$$T_i = \frac{\sum_{i=i}^{i=g} A \times d_i + B \times f_i}{n} \tag{7}$$

where, g is the total number of granules in the input domain (Note that the number of granules for the current task is n for an n processor system).

For example, consider computing hough transform of an edge image to detect line segments. If there exists a line whose normal distance from the origin is r, the normal makes an angle θ with the x-axis then if a point (x,y) lies on that line, the following equation is satisfied.

$$r = x\cos\theta + y\sin\theta$$

r and θ are quantized for desired accuracy and then for each significant pixel (where there is an edge), r is computed for all quantized θ values. If two partitions of equal size contain different number of edge pixels, then the

amount of computation will be different for the two partitions despite them being equal in size. In fact, the computation is directly proportional to the number of edge pixels in a partition. A way to perform static load balancing will be to decompose the input data such that each partition contains equal number of edge pixels. The computation to recognize this partioning can be performed in the task in which edges are detected by keeping a count of the number of edges detected by a processor. Once a task is completed, the data can be reorganized such that the number of edges with each processor is in the interval $(\frac{Z_a}{n} - \delta, \frac{Z_a}{n} + \delta)$, where Z_a is the total number of edges detected in the image, and δ is determined by the minimum granule size from fixed overhead considerations.

3.1.3. Weighted Static

When the computation in a granule not only depends on number of significant data points in the input domain, but it also depends on their spatial relationships, then data distribution needs to be taken into account as a measure of load to perform load balancing. For example, in stereo match or time match, not only does the computation depend on the number of zero crossings, but it also depends on their spatial distribution. If the zero crossings are densely spaced, then the computation will be more than that if the same number of zero crossings are sparsely distributed. The reason is that if the zero crossings are densely packed, then more number of zero crossings need to be matched with each corresponding zero crossing in the other image, whereas less number of zero crossings need to be matched if they are sparsely distributed. Hence, the computation also depends on the spatial density (such as features/row if one dimensional matching is performed). That is,

$$T_i = A \times d_i + B \times w_i \times d_i \tag{8}$$

where, w_i is the feature dependent spatial density. For example, if the minimum granule size is a row of the input data then $w_i = r_i^{\beta}$, where r_i is the number of features in row i, and β is a parameter, $0 \le \beta \le 1$. $\beta = 0$ means that the computation is independent of how the features are distributed within a row. Therefore, to divide the computation equally among n processors, the following heuristic can be used.

$$T_i = \frac{\sum_{i=0}^{i=R} A \times d_i + B \times w_i \times d_i}{n} \tag{9}$$

where, R is the number of rows in the image. Note that the above heuristics approximate the load and do not exactly divide the computation among processors. However, in the next section we will show that these schemes perform well.

3.1.4. Dynamic

Above three methods use the knowledge about the data when it is produced to perform load balancing for the next task. However, once decomposition is done, then the data is not reshuffled. Therefore, we consider the above methods as knowledged based static load balancing schemes. In the dynamic scheme, the data is decomposed into finer granules such that the number of tasks, (that is number of independent granules) M, is much larger than the number of processors.

At execution time the processors are assigned these tasks dynamically by a designated scheduler from a task queue containing these tasks. Processors are assigned new tasks as they finish their previously assigned tasks, if there are more tasks left to be assigned. However, the knowledge obtained from the previous step can be used again to anticipate the completion of a task, in order to assign a new task to a processor. That is, the task assignment can be pipelined, thereby reducing the overhead of dynamic assignment.

The following procedure illustrates the dynamic assignment of tasks onto the processor. The pseudo code essentially illustrates what the scheduler does in order to perform dynamic load balancing. The number of tasks (max_tasks) are determined during the execution of the preceding step in the system, and the task_queue contains all the tasks including the computational information associated with each task. Initially, the scheduler assigns few tasks to each processor. The number of tasks to be assigned initially is a parameter (pipe_line_no). If this parameter is 1, it implies that there is no anticipatory scheduling. In other words, a processor is assinged a new task only when it finishes the task it is currently executing. A task is assigned to a processor only if the task contains significant computation. For example, in stereo match, if a task's data does not contain any zero crossings, then the task can be discarded because it is not going to produce any useful information anyway. In a blind scheme, where little is known about a task, the task will be assigned, which is an overhead, and can be avoided by using the knowledge obtained from the previous steps. Whenever a processor P_i completes the current task, it sends a *compl_msg* to the scheduler which assigns P_i a new task if the task_queue is not empty. Once the task_queue becomes empty, the scheduler sends a *term_msg* (terminate message) to all the processors. Upon receiving a *term_msg* from the scheduler, processors complete the remaining tasks in their task_queues, and sends a *term_msg* to the scheduler, terminating the computation. Note that by using the pipe_line_no, anticipatory dynamic scheduling can be performed, and a processor need not be idle when a new task is being assigned. By using this parameter, the amount of initial static assignment, and dynamic assignment can be controlled.

Dynamic Scheduling of Tasks

```
/*Initial Assignment*/

1.   curr_task = 0;
2.   for j = 1 to j <= pipe_line_no do
3.        for i = 1 to i = num_proc do
4.             if comp(task_queue(curr_task)) > 0
5.                  schedule curr_task at proc. P_i;
6.                  curr_task = curr_task+1;
7.             else
8.                  curr_task = curr_task+1;
9.                  go to 4.
10.            end_if
11.       end_for
12.  end_for

     /*Scheduling*/

13.  done = false; k = num_proc;
14.  while not done do
15.       wait for msg from a processor;
16.       receive msg;
17.       if ( msg = compl_msg )
18.            P_i = sender processor;
19.            if curr_task < max_tasks
20.                 if comp(task_queue(curr_task)) > 0
21.                      schedule curr_task at proc. P_i;
22.                      curr_task = curr_task+1;
23.
24.                 else
25.                      curr_task = curr_task+1;
26.                      go to 19.
27.            else
28.                 send term_msg to P_i.
29.       else if ( msg = term_msg)
30.            k = k - 1;
31.            if (k <= 0)
32.                 done = true.
```

4. Parallel Implementation and Performance Evaluation

This section presents a parallel implementation of the algorithms that are part of motion estimation system and describes the performance of the algorithms and load balancing strategies.

4.1. Hypercube Multiprocessor

A hypercube multiprocessor system of size P has P processors, where P is an integral power of 2. P processors are indexed by the integers 0,...,P-1 and the following criteria is satisfied. If the processor numbers are represented by $\log_2(P)$ bits then two processors are connected by communication links if and only if their bit representation

differs by exactly one bit. Therefore, each processor is connected to $\log_2(P)$ processors with direct communication links. Diameter of the hypercube of size P is $\log_2(P)$ (diameter is the maximum distance between any two nodes). We used Intel ipsc/2 hypercube multiprocessor consisting of 16 nodes. Each node consists of an Intel 80386 processor, Intel 80387 co-processor, 4 megabyte memory, and a communication module.

4.2. Feature Extraction

Features used for stereo match algorithms are the zero crossings of the convolution of the image with Laplacian. Zero crossing computation involves 2-D convolution and extraction of zero crossings from the convolved image. Since convolution is a data independent algorithm uniform partitioning is sufficient to evenly distribute the computation. The mapping is a division of $N \times N$ image onto P processors. Each processor computes the zero crossings of share of N^2/P pixels. Data division onto the processors is done along the rows. This mapping reduces communication to only in one direction. The reason is that 2-D convolution can be broken into two 1-D convolution [7]. This not only reduces the computation from W^2 sum of products operations per pixel to $2 \times W$ sum of product operations per pixel (W is the convolution mask window size), but also reduces the communication requirements in a parallel implementation if the data partitioning is done along the rows. There is no need for communication when convolution is performed along the rows.

Table 1 shows the performance results for the above implementation for an image of size 256×256 and convolution window of size 20×20. First column shows the number of processors in the cube(P). Second column represents the total processing time (t_{proc}) for convolution. Column 3 shows the number of bytes communicated by a processor to the neighboring processor, and column 4 shows the corresponding communication time which is small compared to the computation time. The second half of the table shows the computation time for extracting zero crossings from the convolved image. Corresponding speedups are also shown.

It can be observed that almost linear speedup is obtained for convolution. Two factors which contribute toward this result are that communication overhead is relatively small, and communication is constant as the number of processors increases. However, the speedup obtained in the elapsed time, which includes the program and data load time also, is sub-linear due to the following reason. The hypercube multiprocessor's host does not have a broadcast capability, and therefore, the overhead of loading the program increases linearly with the number of processors. However, data load time increment with the increase in the number of processors is comparatively small because amount of data to be loaded to one processor decreases as the number of processors increases. The only

Table 1 : Performance for feature Extraction (Zero Crossings)

Computation for Convolution and Zero Crossings							
	Convolution Window Size = 20x20						
No. Proc.	Conv. Comp. Time(sec.)	Conv. Comm. Bytes	Conv. Comm. Time(ms.)	Conv. Total Time(sec.)	Conv. Speed Up	ZC Comp. Time(sec.)	ZC Speed Up
1	109.0	0	0	109.0	1	6.47	1
2	54.76	2816	13	54.78	1.98	3.23	1.99
4	27.51	5632	36	27.55	3.95	1.66	3.89
8	13.88	5632	36	13.92	7.83	0.85	7.60
16	7.07	5632	36	7.11	15.33	0.42	15.25

Feature Extraction Performance (Elapsed Time)		
No. Proc.	Elapsed Time(sec.)	Speed up
1	116.2	1
2	58.8	1.97
4	30.1	3.86
8	16.1	7.22
16	9.6	12.1

increment in data load time results from the number of communication setups from the host to the node processors, which increases linearly with the number of processors.

4.3. Matching Features

This task involves matching features in stereo pair of images. Since the imaging setup uses the parallel axis method, the epipolar constraint is used to limit the search space for matching to one-dimension which is in the horizontal direction. Thus data partioning along the rows for parallel implementation results in no communication between node processors as long as each partition contains an integral number of rows.

The computation involved in stereo matching algorithm is data dependent. The computation varies across the image because it depends on the number of zero crossings, distribution of zero crossing across the image, and distribution of zero crossings along the epipolar lines. Therefore, partioning the data uniformly among the processors (i.e. assign each processor equal number of rows) may not yield expected speedups and processor utilization. A processor which has very few zero crossings, and sparsely distributed zero crossings will be under utilized, whereas a processor with a large number of zero crossings, and densely distributed zero crossings will become a bottleneck.

We used uniform partitioning, static load balancing, weighted static and dynamic load balancing schemes to decompose the computation on the multiprocessor. Static load balancing can be achieved by keeping a count of the zero crossings with each processor when the previous task (feature extraction) is executed. At the completion of the

task, the data is reorganized using this information, and using the techniques described in the previous section.

Figure 5 shows the distribution of the computation times for 8 processor case. The X-axis shows the processor number, and the Y-axis shows the computation time for each scheme. As we can observe, uniform partitioning does not perform well at all because the variation in computation time is tremendous, and therefore, performance gains are minimal. The static load balancing scheme (shown as dashed bars) performs much better than uniform partitioning, but variation in computation times is still significant because the computation also depends on the distribution of zero crossings. The weighted static scheme performs better than static, and further reduces the variation in computation times. Note that these schemes only measure the load approximately, and therefore, will not divide the computation exactly uniformly. Furthermore, minimum granularity is a row boundary in order to avoid communication between processors. Finally, for 8 processor case, dynamic scheme performs the best. Table 2 summarizes the distribution for the 8 processor case. The Table shows the computation time, variation ratio, and improvement ratio for each processor under all four methods. Table 2 summarizes the distribution for the 8 processor case. The table

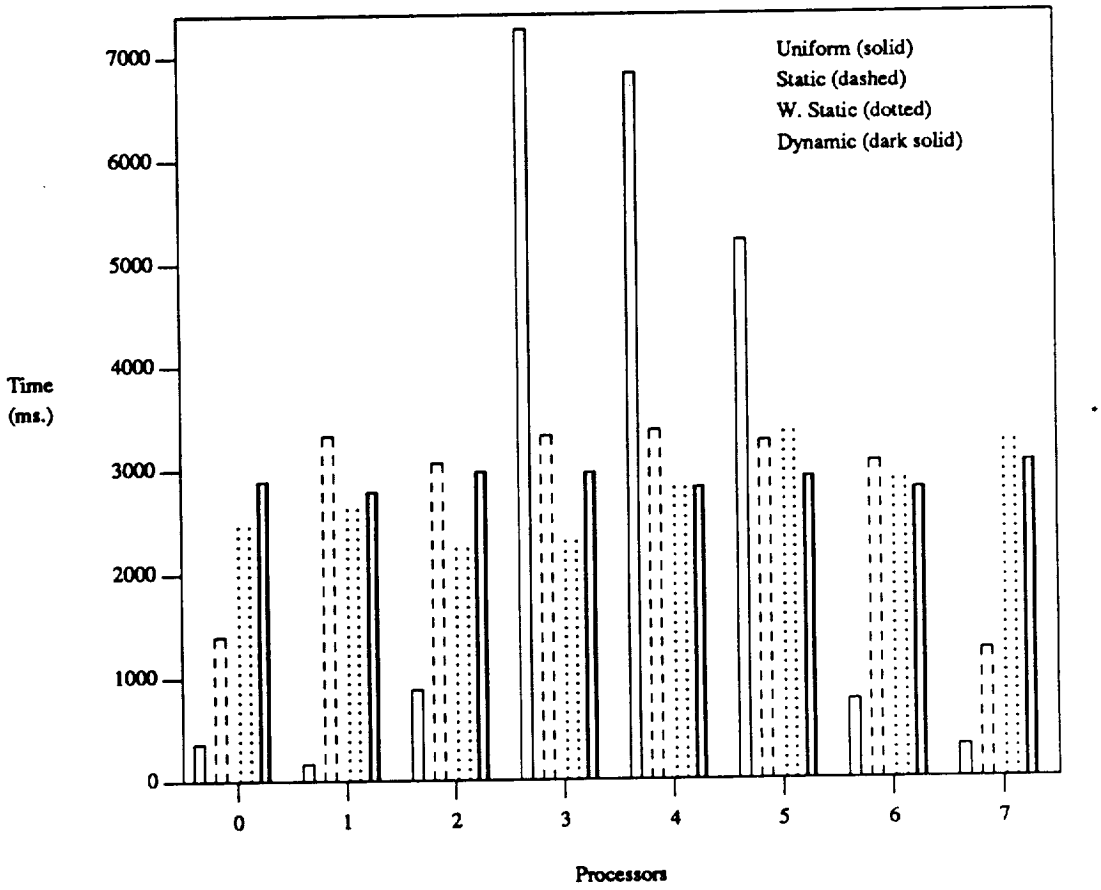


Figure 5 : Distribution of Computation Times for Stereo Match (P=8)

shows the computation time for each processor for all four methods. For example, the variation ratio is 44.25 for uniform partitioning, is 2.71 for static load balancing, is 1.50 for weighted static, and is 1.09 for dynamic load balancing. Improvement ratio is the ratio of speedup obtained with load balancing to that of uniform partitioning. The computation times shown include all the overhead of load balancing schemes. Figure 6 shows the speedup graph for varying size of multiprocessor from 1 processor to 16. We observe that uniform partitioning does not provide any significant gains in speedup as the number of processors increases. Dynamic scheme performs the best among all the schemes, and the two static scheme perform comparably with the dynamic scheme. We believe that as the number of processors is increased, the two static schemes will move even closer to dynamic scheme, or even perform better than the dynamic scheme, because for a larger multiprocessors, the overhead of dynamic scheme will be greater.

4.4. Time Match

The computation in time match algorithm is similar to that in stereo match except the search space is two-dimensional, and the input to the algorithm is stereo match output. Other difference is that the number of significant points in the input data is much smaller than that in stereo match, because a great deal of input points get eliminated in stereo match. Table 3 shows the distribution of the computation times for the 16 processor case. We only present uniform partitioning and static load balancing cases. The most important observation is that uniform partitioning

Table 2 : Distribution of Computation Times for Stereo Match

Computation Time Distribution for Stereo Match (P=8)				
Proc. No.	Uniform Partitioning	Static	Static Weighted	Dynamic
	Time (ms.)	Time (ms.)	Time (ms.)	Time (ms.)
0	364	1402	2439	2890
1	164	3333	2606	2786
2	878	3066	2219	2980
3	7258	3327	2277	2967
4	6827	3371	2798	2818
5	5207	3269	3328	2913
6	762	3063	2864	2803
7	312	1243	3223	3051
Max.	7258	3371	3328	3051
Min.	164	1243	2219	2786
Variation ratio	44.25	2.71	1.50	1.09
Improvement ratio	1	2.15	2.19	2.38

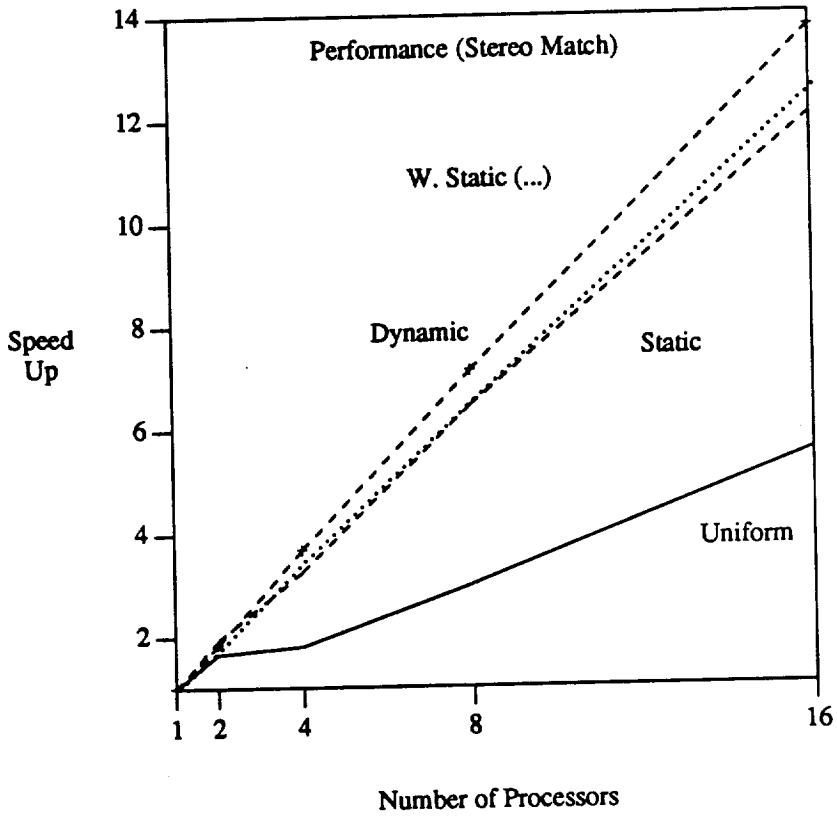


Figure 6 : Speedups for Stereo Match Computation

performs worse than that in the case of stereo match, and static load balancing performs better.

The Table shows how the measure of computation (number of zero crossings left from stereo match step) is divided among the processors in the two cases. It is clear that the number of zero crossings are very evenly distributed (within the minimum granule of one row constraint) in the static case, whereas they are lumped with a few processors in the uniform partitioning case. Figure 7 shows the speedup graphs for the two schemes for a range of multiprocessor size. The speedup gains for the load balanced case is very significant over the uniform partitioning case. We computed the overhead of performing knowledge based static load balancing, and the overhead was 3 ms., which is negligible compared to the computation time, and the performance gains are significant.

4.5. Second Stereo Match

This step involves stereo match computation for features from images at time instant t_{i+1} after time point correspondence is established between images at time t_i and t_{i+1}. The matching is similar to that in first stereo match except that it need to be done only at those points at which time correspondence has already been established.

Table 3 : Distribution of Computation Time for Time Match

Computation for Time Match (Proc. = 16)						
Proc. No.	Uniform Partitioning			With Load Balancing		
	Matching (Sec.)	Total (Sec.)	No. Zcs	Matching (Sec.)	Total (Sec.)	No. Zcs
0	0.14	0.22	3	9.35	10.00	47
1	0.03	0.14	2	12.38	12.55	50
2	0.02	0.13	0	13.12	13.21	53
3	0.02	0.13	0	14.23	14.27	43
4	0.02	0.13	0	11.88	11.91	45
5	3.61	3.72	21	10.93	10.95	44
6	13.45	13.56	55	12.82	12.85	53
7	5.09	5.20	20	12.16	12.19	51
8	26.65	26.76	93	11.41	11.44	45
9	45.85	45.97	182	10.63	10.65	40
10	73.82	73.93	259	13.89	13.91	50
11	27.20	27.32	121	13.69	13.71	44
12	0.31	0.42	3	15.07	15.09	43
13	0.11	0.22	1	15.70	15.72	56
14	0.42	0.53	4	14.36	14.39	56
15	0.08	0.10	0	5.21	5.68	43
	Max. time(sec.)	Min. time(sec.)	Variation ratio	Speed up	Improvement ratio	
Uniform	73.82	0.10	738	2.69		
Balanced	15.72	5.68	2.76	12.63	4.7	

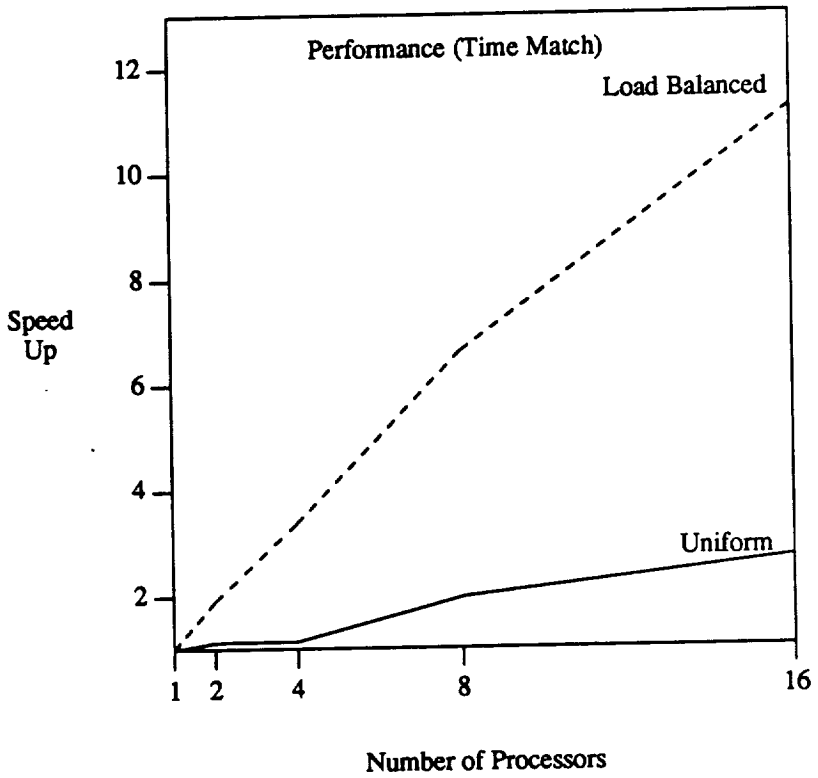


Figure 7 : Speedup for Time Match

Consequently, the number of features to be matched are much less than that in the first computation, and hence, the importance of load balancing is further increased. Figure 8 depicts the distribution of computation times for the second stereo match step. The three load balancing algorithms used in this case are Uniform Partitioning, Static and Dynamic. We observe from the Figure that uniform partitioning does not perform well compared to the other two schemes. The variation in computation time is significant, and the static and dynamic schemes perform comparably.

Figure 9 presents the speedups for the same algorithm for various multiprocessor sizes. The Figure shows that the gains from these load balancing schemes are very significant over uniform partitioning. One important observation can be made by comparing results in Figure 6 and 9. Note that the performance of uniform partitioning in the second stereo match is much worse than that in the first stereo match. For example, for 16 processor case, the speedup in the first case is 5.55, whereas for the same multiprocessor size speedup is only approximately 2.3 for the second stereo match. Therefore, as the computation progresses in an integrated environment, the gains of these load balancing schemes become increasingly significant.

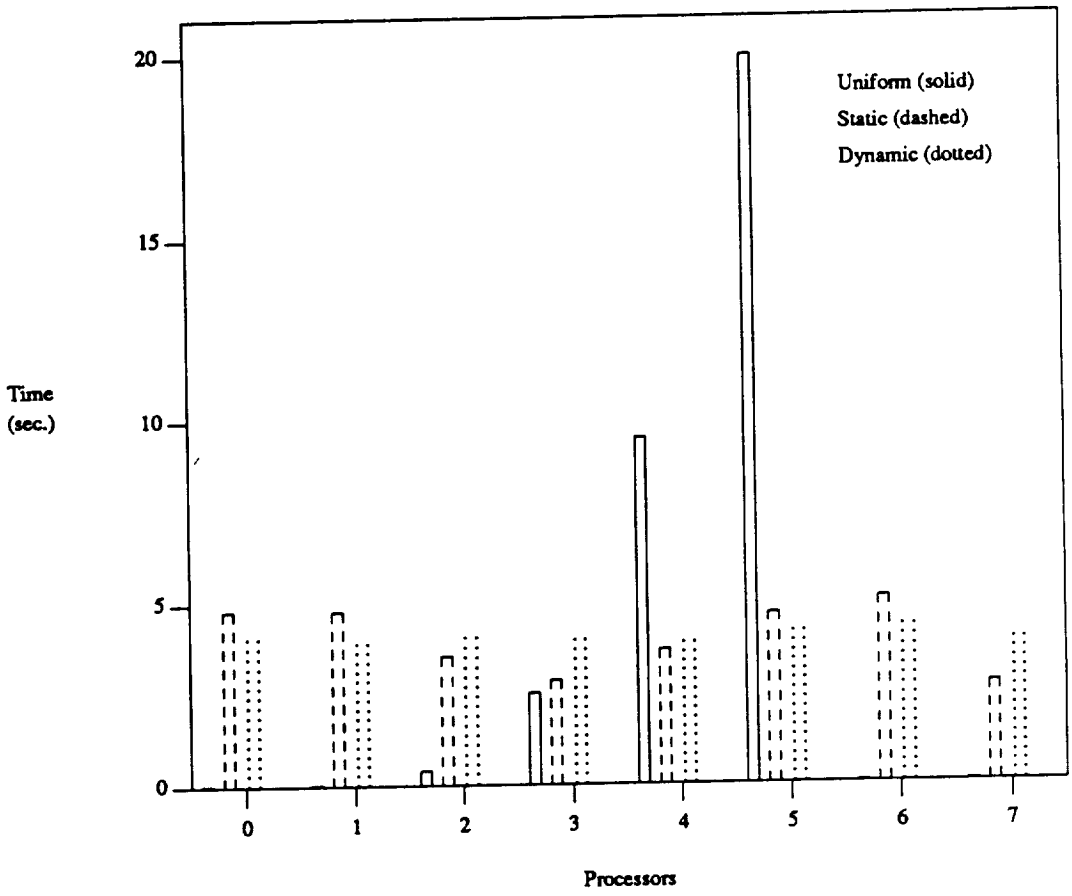


Figure 8 : Distribution of Computation Times for Second Stereo Match (P=8)

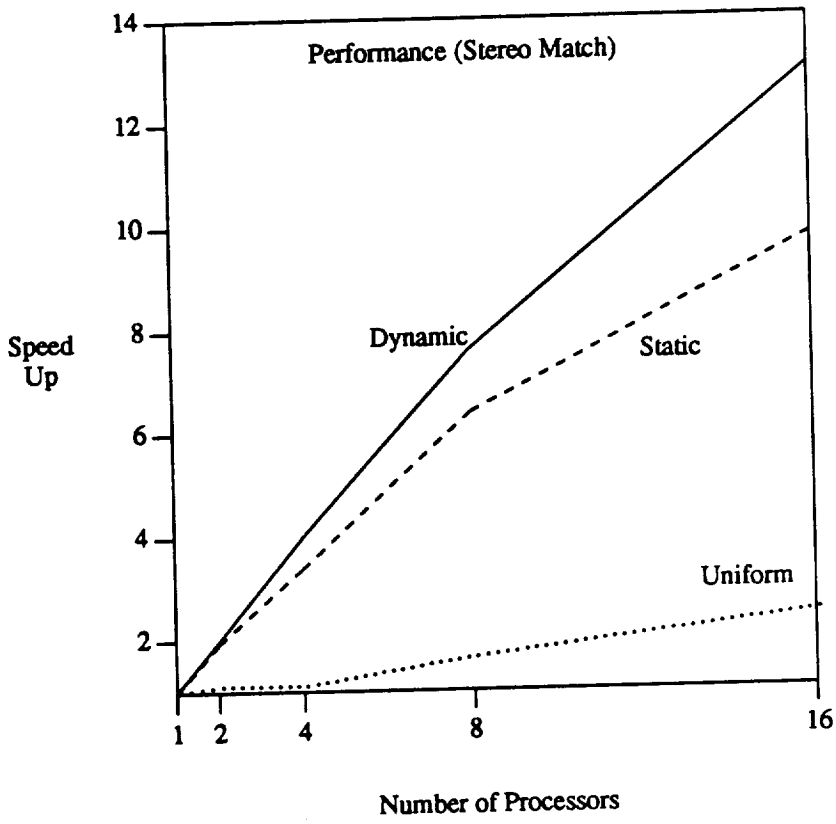


Figure 9 : Speedups for Second Stereo Match

4.6. Summary of Results

In summary, the following important observations can be made from the results presented in this section. First, the improvement in performance (such as utilization and speedup) itself increases using the load balancing schemes as the number of processors increases. Therefore, performance gains are expected to be higher for larger multiprocessors. Second, in an integrated environment, the overheads of such methods are small because measure of load can be computed at run time as a bi-product of the current task. Finally, though we showed the performance results of the implementation on the hypercube multiprocessor, these methods can be applied when algorithms are mapped on any medium to large grain multiprocessor system, because these techniques are independent of the underlying multiprocessor architecture.

Consider the overall performance gains for the entire system. As the computation progresses from one step to the next, uniform partitioning performs worse because the data points reduce, but the computation at each point increases. Hence, the gains of using parallel processing are minimal. However, the load balancing techniques recognize the data distribution at each step, and the data is decomposed using the distribution. Therefore, performance

gains are expected to improve as the computation progresses in an integrated environment. For example, consider zero crossing, stereo match, time match, and second stereo match steps. In zero crossing computation, uniform partitioning performs well and load is balanced. Hence, the improvement ratio is 1. For stereo match the improvement of static over uniform partitioning is 2.15 for 8 processor case, and is 2.22 for 16 processor case. Similarly, for time match step, the improvement of static load balancing for 8 processor case is 3.38, and for 16 processor case, it is 4.2. Therefore, the improvement in performance itself increases as the number of processors increases as well as when the computation progresses in from one step to the next in a vision system.

5. Concluding Remarks

In this paper we presented techniques to perform efficient data decomposition and load balancing for vision systems, for medium to large grain parallelism. Two important characteristics of these techniques are that they are general enough to apply to any such integrated system, and that they use statistics and knowledge from the execution of a task to perform data decomposition and load balancing for the next task in the system. Knowledge from each step is used to perform load balancing in the next step. The advantages of such schemes are as follows. First, these techniques use characteristics of the tasks and the data, and therefore, work well no matter how the data changes. Secondly, many vision systems consist of such tasks and exhibit the above described computation flow, and therefore, these techniques can be used in any system.

Finally, the performance of the proposed techniques was evaluated by using a parallel implementation of the motion estimation system algorithms on a hypercube multiprocessor system. The results show that using uniform partitioning without considering the computations involved, parallel processing does not provide significant performance improvements over sequential processing. Furthermore, by applying the proposed data decomposition and load balancing techniques significant performance gains (as much as 6 fold) can be obtained over uniform partitioning.

REFERENCES

[1] C. Weems, A. Hanson, E. Riseman, and A. Rosenfeld, "An integrated image understanding benchmark: recognition of a 2 1/2 D mobile," in *International Conference on Computer Vision and Pattern Recognition*, Ann Arbor, MI, June 1988.

[2] Alok N. Choudhary, "Parallel architectures and parallel algorithms for integrated vision systems," in *Ph.D. Thesis*, University of Illinois, Urbana-Champaign, Agust 1989.

[3] Mun K. Leung and Thomas S. Huang, "Point matching in a time sequence of stereo image pairs," in *Tech. Rep., CSL, University of Illinois*, Urbana-Champaign, 1987.

[4] M. K. Leung, A. N. Choudhary, J. H. Patel, and T. S. Huang, "Point matching in a time sequence of stereo image pairs and its parallel implementation on a multiprocessor," in *IEEE Workshop on Visual Motion*, Irvine, CA, March 1989.

[5] Alok N. Choudhary, Subhodev Das, Narendra Ahuja, and Janak H. Patel, "Surface reconstruction from stereo images : an implementation on a hypercube multiprocessor," in *The Fourth Conference on Hypercubes, Concurrent Computers, and Applications*, Monterey, CA, March 1989.

[6] K. S. Arun, T. S. Huang, and S. D. Blostein, "Least-sqaure fitting of two 3-D point sets," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 9, pp. 698-700, September 1987.

[7] A. Huertas and G. Medioni, "Detection of intensity changes with subpixel accuracy using Laplacian-Gaussian masks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, pp. 651-664, September 1986.

[8] Y. C. Kim and J. K. Aggarwal, "Positioning 3-D objects using stereo images," *Computer and Vision Research Center, The University of Texas at Austin.*