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PROCESSING PANORAMA VIDEO IN REAL-TIME

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There are many scenarios where high resolution, wide field of view video is useful. Such panorama video may be generated using camera arrays where the feeds from multiple cameras pointing at different parts of the captured area are stitched together. However, processing the different steps of a panorama video pipeline in real-time is challenging due to the high data rates and the stringent timeliness requirements. In our research, we use panorama video in a sport analysis system called Bagadus. This system is deployed at Alfheim stadium in Tromsø, and due to live usage, the video events must be generated in real-time. In this paper, we describe our real-time panorama system built using a low-cost CCD HD video camera array. We describe how we have implemented different components and evaluated alternatives. The performance results from experiments ran on commodity hardware with and without co-processors like graphics processing units (GPUs) show that the entire pipeline is able to run in real-time.

Keywords: Real-time panorama video; system integration; camera array.

1. Introduction

A wide field of view (panoramic) image or video is often used in applications like surveillance, navigation, scenic views, educational exhibits and sports analysis. Here, video feeds are often captured using multiple cameras capturing slightly overlapping areas, and the frames are processed and stitched into a single unbroken frame of the whole surrounding region. To prepare the individual frames for stitching and finally generating the panorama frame, each individual frame must be processed for barrel distortion, rotated to have the same angle, warped to the same plane and corrected for color differences. Then, the frames are stitched to one large panorama image, where the stitch operation also includes searching for the best possible seam in the

overlapping areas to avoid seams through objects of interest in the video. Finally, the panorama frame is encoded to save storage space and transfer bandwidth and, written to disk. As several of these steps include direct pixel manipulation and movement of large amounts of data, the described process is very resource hungry.

In [30], we described our implementation of a real-time panorama video pipeline for an arena sports application called Bagadus [11, 28], and this is an extended version providing more details. In our panorama setup, we use a static array of low-cost CCD HD video cameras, each pointing at a different direction, to capture the wide field of view of the arena. These different views are slightly overlapped in order to facilitate the stitching of these videos to form the panoramic video. Several similar non-real-time stitching systems exist (e.g., [23]), and a simple non-real-time version of this system has earlier been described and demonstrated at the functional level [11, 26]. Our initial prototype is the first sports application to successfully integrate per-athlete sensors [17], an expert annotation system [16] and a video system, but due to the non-real-time stitching, the panorama video was only available to the coaches some time after a game. The first prototype also did not use any form of color correction or dynamic seam detection. Hence, the static seam did not take into account moving objects (such as players), and the seam was

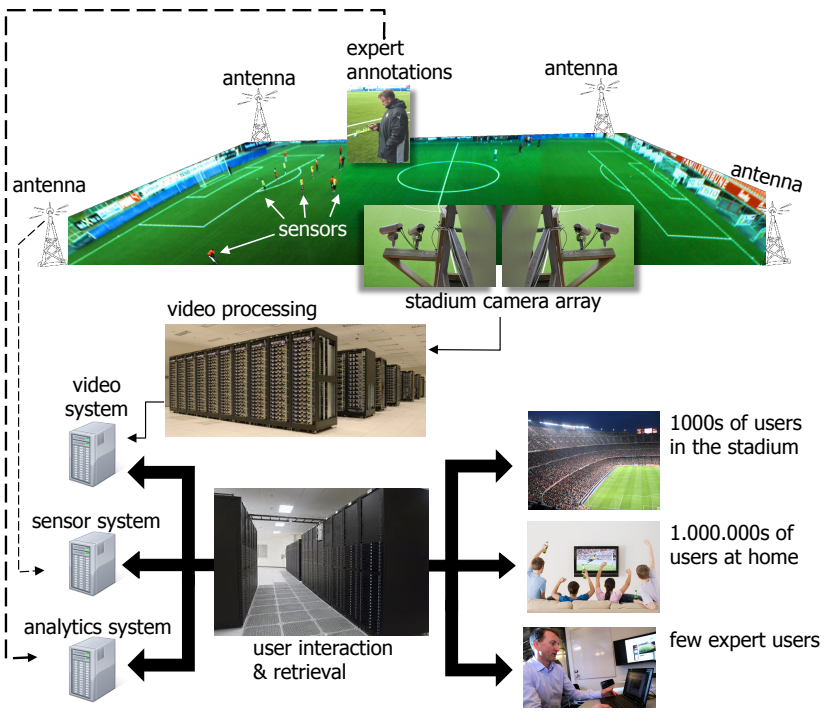


Figure 1. Overall system architecture.

therefore very visible. However, new requirements like real-time performance and better visual quality have resulted in a new and improved pipeline. Using our new real-time pipeline, such systems can be used during the game. A brief overview of the architecture and interaction of the different components is given in figure 1. In this paper we will focus on the details of the whole pipeline from capturing images from the cameras via various corrections steps for panorama generation to encoding and storage of both the panorama video and the individual camera streams on disks. We describe how we have evaluated different implementation alternatives (both algorithms and implementation options), and we benchmark the performance with and without using graphics processing units (GPUs) as an co-processors. We evaluate each individual component, and, we show how the entire pipeline is able to run in real-time on a low-cost 6-core machine with a GPU, i.e., moving the 1 frame per second (fps) system to 30 fps enabling game analysis during the ongoing event.

The remainder of the paper is structured as follows. We give a brief overview of the basic idea of our system in section 2, and then we analyze the state of the art in section 3 to see if systems exist that meet our requirements. Then, we describe and evaluate our real-time panorama video pipeline in section 4. Various aspect of the system are discussed in section 5 before we finally conclude the paper in section 6.

2. Our sports analysis systems

Today, a large number of (elite) sports clubs spend a large amount of resources to analyze their game performance, either manually or using one of the many existing analytics tools. For example, in the area of soccer, several systems enable trainers and coaches to analyze the gameplay in order to improve the performance. For instance, Interplay-sports, ProZone, STATS SportVU Tracking Technology and Camargus provide very nice video technology infrastructures. These systems can present player statistics, including speed profiles, accumulated distances, fatigue, fitness graphs and coverage maps using different charts, 3D graphics and animations. Thus, there exist several tools for soccer analysis. However, to the best of our knowledge, there does not exist a system that fully integrates all desired features in real-time, and existing systems still require manual work moving data between different components. In this respect, we have presented Bagadus [11, 26], which integrates a camera array video capture system with a sensor-based sport tracking system for player statistics and a system for human expert annotations. Our system allows the game analytics to automatically playout a tagged game event or to extract a video of events extracted from the statistical player data. This means that we for example can query for all sprints faster than X or all situations where a player is in the center circle. Using the exact player position provided by sensors, a trainer can also follow individuals or groups of players, where the videos are presented either using a stitched panorama view of the entire field or by (manually or automatically) switching between the different camera views. Our prototype is currently deployed at an elite club stadium. We use a dataset captured at a premier

league game to experiment and to perform benchmarks on our system. In previous versions of the system, the panorama video had to be generated offline, and it had static seams [11]. For comparison with the new pipeline presented in section 4, we next present the camera setup and the old pipeline.

2.1. *Camera setup*

To record the high resolution video of the entire soccer field, we have installed a camera array consisting of four Basler industry cameras with a 1/3-inch image sensors supporting 30 fps at a resolution of 1280×960. The cameras are synchronized by an external trigger signal in order to enable a video stitching process that produces a panorama video picture. The cameras are mounted close to the middle line (see figure 2), i.e., under the roof of the stadium covering the spectator area approximately 10 meters from the side line and 10 meters above the ground. With a 3.5 mm wide-angle lens, each camera covers a field-of-view of about 68 degrees, and the full field with sufficient overlap to identify common features necessary for camera calibration and stitching, is achieved using the four cameras. Calibration is done via a classic chessboard pattern [33].

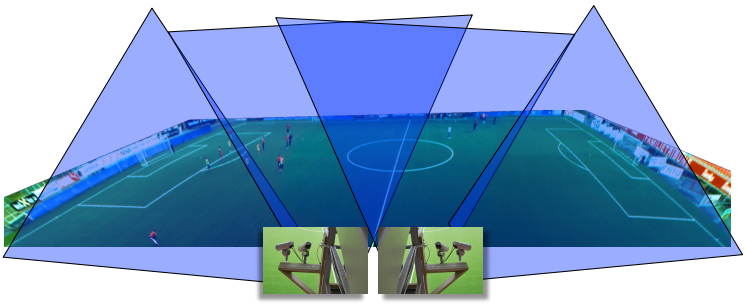


Figure 2. Camera setup at the stadium.

2.2. *The offline, static stitching pipeline*

Our first prototype focused on integrating the different subsystems. We therefore did not put large efforts into real-time performance resulting in an unoptimized, offline panorama video pipeline that combined images from multiple, trigger-synchronized cameras as described above. The general steps in this stitching pipeline are: 1) correct the images for lens distortion in the outer parts of the frame due to a wide-angle fish-eye lens; 2) rotate and morph the images into the panorama perspective caused by different positions covering different areas of the field; 3) rotate and stitch the video images into a panorama image; and 4) encode and store the stitched video to persistent storage. Several implementations were tested for the stitching operation

such as the OpenCV planar projection, cylindrical projection and spherical projection algorithms, but due to the processing performance and quality of the output image, the used solution is a homography based algorithm.

The first step before executing the pipeline, is to find corresponding pixel points in order to compute the homography between the camera planes [12], i.e., the head camera plane and the remaining camera planes. When the homography is calculated, the image can be warped (step 2) in order to fit the plane of the second image. The images must be padded to have the same size, and the seams for the stitching must be found in the overlapping regions (our first pipeline used static seams). Figure 3 shows the four rotated, wrapped and stitched images. The whole process of stitching the images is described in [28]. We also calculate the homography between the sensor data plane and the camera planes to find the mapping between sensor data coordinates and pixel positions.

Figure 3. The homography-based panorama image stitched from four cameras

As can be seen in the figure, the picture is not perfect, but the main challenge is the high execution time. On an Intel Core i7-2600 @ 3.4 GHz and 8 GB memory machine, the stitching operation consumed 974 ms of CPU time to generate each 7000x960 pixel panorama image [11]. Taking into account that the target display rate is 30 fps, i.e., requiring a new panorama image every 33 ms, there are large performance issues that must be addressed in order to bring the panorama pipeline from a 1 fps system to a 30 fps system. However, the stitching operations can be parallelized and parts of it offloaded to external devices such as GPUs, which, as we will see in section 4, results in a performance good enough for real-time, online processing and generation of a panorama video.

3. Related work

Real-time panorama image stitching is becoming common. For example, many have proposed systems for panorama image stitching (e.g., [6, 14, 19–21]), and modern operating systems for smart phones like Apple iOS and Google Android support generation of panorama pictures in real-time. However, the definition of real-time is not necessarily the same for all applications, and in this case, real-time is similar to "within a second or two". For video, real-time has another meaning, and a panorama picture must be generated in the same speed as the display frame rate, e.g., every 33 ms for a 30 frame-per-second (fps) video.

One of these existing systems is Camargus [1]. The people developing this system claim to deliver high definition panorama video in real-time from a setup consisting of 16 cameras (ordered in an array), but since this is a commercial system, we have no insights to the details. Another example is Immersive Cockpit [29] which aims to generate a panorama for tele-immersive applications. They generate a stitched video which capture a large field-of-view, but their main goal is not to give output with high visual quality. Although they are able to generate video at a frame rate of about 25 fps for 4 cameras, there are visual limitations to the system, which makes the system not well suited for our scenario.

Moreover, Baudisch et al. [5] present an application for creating panoramic images, but the system is highly dependent on user input. Their definition of real time is "panorama construction that offers a real-time preview of the panorama while shooting", but they are only able to produce about 4 fps (far below our 30 fps requirement). A system similar to ours is presented in [4], which computes stitchmaps on a GPU, but the presented system produces low resolution images (and is limited to two cameras). The performance is within our real-time requirement, but the timings are based on the assumption that the user accepts a lower quality image than the cameras can produce.

Haynes [3] describes a system by the Content Interface Corporation that creates ultra high resolution videos. The Omnicam system from the Fascinate [2,27] project also produces high resolution videos. However, both these systems use expensive and specialized hardware. The system described in [3] also makes use of static stitching. A system for creating panoramic videos from already existing video clips is presented in [7], but it does not manage to create panorama videos within our definition of real-time. As far as we know, the same issue of real-time is also present in [5,13,23,31].

In summary, existing systems (e.g., [7,13,23,29,31]) do not meet our demand of being able to generate the video in real-time, and commercial systems (e.g., [1,3]) as well as the systems presented in [2,27] do often not fit into our goal to create a system with limited resource demands. The system presented in [4] is similar to our system, but we require high quality results from processing a minimum of four cameras streams at 30 fps. Thus, due to the lack of a low-cost implementations fulfilling our demands, we have implemented our own panorama video processing pipeline which utilize processing resources on both the CPU and GPU.

4. A real-time panorama stitcher

In this paper, we do not focus on selecting the best algorithms etc., as this is mostly covered in [11]. The focus here is to describe the panorama pipeline and how the different components in the pipeline are implemented in order to run in real-time. We will also point out various performance trade-offs.

As depicted in figure 4, the new and improved panorama stitcher pipeline is separated into two main parts: one part running on the CPU, and the other running

on a GPU using the CUDA framework. The decision of using a GPU as part of the pipeline was due to the potential high performance and the parallel nature of the workload. The decision of using the GPU for the pipeline has affected the architecture to a large degree. Unless otherwise stated (we have tested several CPUs and GPUs), our test machine for the new pipeline is an Intel Core i7-3930K, i.e., a 6-core processor based on the Sandy Bridge-E architecture, with 32 GB RAM and an Nvidia GeForce GTX 680 GPU based on the GK104 Kepler architecture.

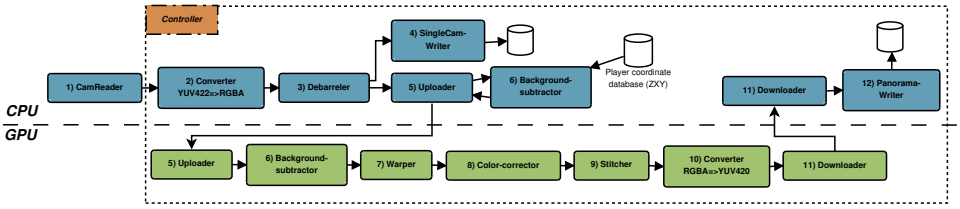


Figure 4. Panorama stitcher pipeline architecture. The orange and blue components run in the CPU and the green components run on the GPU.

4.1. *The Controller module*

The single-threaded Controller is responsible for initializing the pipeline, synchronizing the different modules, handling global errors and frame drops, and transferring data between the different modules. After initialization, it will wait for and get the next set of frames from the camera reader (CamReader) module (see below). Next, it will control the transfers of data from the output buffers of module N to the input buffers of module $N+1$. This is done primarily by pointer swapping, and with memory copies as an alternative. It then signals all modules to process the new input and waits for them to finish processing. Next, the controller continues looping by waiting for the next set of frames from the reader. Another important task of the Controller is to check the execution speed. If an earlier step in the pipeline runs too slow, and one or more frames has been lost from the cameras, the controller will tell the modules in the pipeline to skip the delayed or dropped frame, and reuse the previous frame.

4.2. *The CamReader module*

The CamReader module is responsible for retrieving frames from the cameras. It consists of one dedicated reader thread per camera. Each of the threads will wait for the next frame, and then write the retrieved frame to a output buffer, overwriting the previous frame. The cameras provide a single frame in YUV 4:2:2 format, and the retrieval rate of frames in the CamReader is what determines the real time threshold for the rest of the pipeline. As described above, the camera shutter

synchronization is controlled by an external trigger box, and in our current configuration, the cameras deliver a frame rate of 30 fps, i.e., the real-time threshold and the CamReader processing time are thus 33 ms.

4.3. *The Converter module*

The CamReader module outputs frames in YUV 4:2:2 format. However, the stitching pipeline requires RGBA internally for processing, and the system therefore converts frames from YUV 4:2:2 to RGBA. This is handled by the Converter module using *ffmpeg* and *swscale*. The processing time for these conversions on the CPU, as seen later in figure 11, is well below the real-time requirement, so this operation can run as a single thread.

4.4. *The Debarreler module*

Due to the wide angle lenses used with our cameras in order to capture the entire field, the images delivered are suffering from barrel distortion which needs to be corrected. We found the performance of the existing debarreling implementation in the old stitching pipeline to perform fast enough. The Debarreler module is therefore still based on OpenCVs debarreling function, using nearest neighbor interpolation, and is executing as a dedicated thread per camera.

4.5. *The SingleCamWriter module*

In addition to storing the stitched panorama video, we also want to store the video from the separate cameras. This storage operation is done by the SingleCamWriter, which is running as a dedicated thread per camera. As we can see in [11], storing the videos as raw data proved to be impractical due to the size of uncompressed raw data. The different CamWriter modules (here SingleCamWriter) therefore encode and compress frames into 3 seconds long H.264 files, which proved to be very efficient. Due to the use of H.264, every SingleCamWriter thread starts by converting from RGBA to YUV 4:2:0, which is the required input format by the x264 encoder. The threads then encode the frames and write the results to disk.

4.6. *The Uploader module*

Due to the large potential of parallelizing the panorama workload and the high computing power of modern GPUs, large parts of our pipeline run on a GPU. We therefore need to transfer data from the CPU to the GPU, i.e., a task performed by the Uploader module. In addition, the Uploader is also responsible for executing the CPU part of the BackgroundSubtractor (BGS) module (see section 4.7). The Uploader consists of a single CPU thread, that first runs the player pixel lookup creation needed by the BGS. Next, it transfers the current RGBA frames and the corresponding player pixel maps from the CPU to the GPU. This is done by use of double buffering and asynchronous transfers.

4.7. *The BackgroundSubtractor module*

Background subtraction is the process of determining which pixels of a video that belong to the foreground and which pixels that belong to the background. The BackgroundSubtractor module, running on the GPU, generates a foreground mask (for moving objects like players) that is later used in the Stitcher module later to avoid seams in the players. Our BackgroundSubtractor can run like traditional systems searching the entire image for foreground objects. However, we can also exploit information gained by the tight integration with the player sensor system. In this respect, through the sensor system, we know the player coordinates which can be used to improve both performance and precision of the module. By first retrieving player coordinates for a frame, we can then create a player pixel lookup map, where we only set the players pixels, including a safety margin, to 1. The creation of these lookup maps are executed on the CPU as part of the Uploader. The BGS on GPU then uses this lookup map to only process pixels close to a player, which reduces the GPU kernel processing times, from 811.793 microseconds to 327.576 microseconds on average on a GeForce GTX 680. When run in a pipelined fashion, the processing delay caused by the lookup map creation is also eliminated. The sensor system coordinates are retrieved by a dedicated slave thread that continuously polls the sensor system database for new samples.

Even though we enhance the background subtraction with sensor data input, there are several implementation alternatives. When determining which algorithm to implement, we evaluated two alternatives: Zivkovic [34, 35] and KaewTraKulPong [18]. Even though the CPU implementation was slower (see figure 5), Zivkovic provided the best visual results, and was therefore selected for further modification. Furthermore, the Zivkovic algorithm proved to be fast enough when modified with input from the sensor system data. The GPU implementation, based on [25], proved to be even faster, and the final performance numbers for a single camera stream can be seen in figure 5. A visual comparison of the unmodified Zivkovic implementation and the sensor system-modified version is seen in figure 6 where the sensor coordinate modification reduce the noise as seen in the upper parts of the pictures.

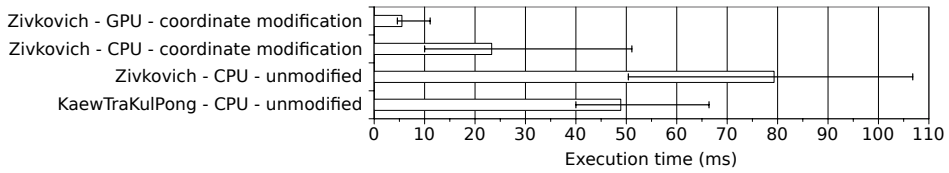
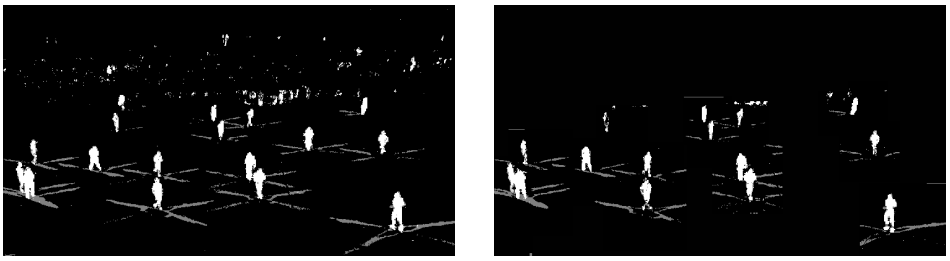


Figure 5. Execution time of alternative algorithms for the BackgroundSubtractor module (1 camera stream).



(a) Unmodified Zivkovic. (b) Player sensor data modification of Zivkovic.

Figure 6. Background subtraction comparison.

4.8. *The Warper module*

The Warper module is responsible for warping the camera frames to fit the stitched panorama image. By warping we mean twisting, rotating and skewing the images to fit the common panorama plane. Like we have seen from the old pipeline, this is necessary because the stitcher assumes that its input images are perfectly warped and aligned to be stitched to a large panorama. Executing on the GPU, the Warper also warps the foreground masks provided by the BGS module. This is because the Stitcher module at a later point will use the masks and therefore expects the masks to fit perfectly to the corresponding warped camera frames. Here, we use the Nvidia Performance Primitives library (NPP) for an optimized implementation.

4.9. *The Color-corrector module*

When recording frames from several different cameras pointing in different direction, it is nearly impossible to calibrate the cameras to output the exact same colors due to the different lighting conditions. This means that, to generate the best panorama videos, we need to correct the colors of all the frames to remove color disparities. In our panorama pipeline, this is done by the Color-corrector module running on the GPU.

We choose to do the color correction after warping the images. The reason for this is that locating the overlapping regions is easier with aligned images, and the overlap is also needed when stitching the images together. This algorithm is executed on the GPU, enabling fast color correction within our pipeline. The implementation is based on the algorithm presented in [32], but have some minor modifications. We calculate the color differences between the images for every single set of frames delivered from the cameras. Currently, we color-correct each image in a sequence, meaning that each image is corrected according to the overlapping frame to the left. The algorithm implemented is easy to parallelize and does not make use of pixel to pixel mapping which makes it well suited for our scenario. Figure 7 shows a comparison between running the algorithm on the CPU and on a GPU.

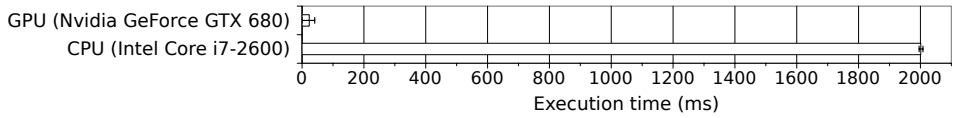


Figure 7. Execution time of color correction.

4.10. *The Stitcher module*

Like in the old pipeline, we use a homography based stitcher where we simply create seams between the overlapping camera frames, and then copy pixels from the images based on these seams. These frames need to follow the same homography, which is why they have to be warped. Our old pipeline used static cuts for seams, which means that a fixed rectangular area from each frame is copied directly to the output frame. Static cut panoramas are faster, but can introduce graphical errors in the seam area, especially when there are movement in the scene (illustrated in figure 4.10).

To make a better seam with a better visual result, we therefore introduce a dynamic cut stitcher instead of the old static cut. The dynamic cut stitcher creates seams by first creating a rectangle of adjustable width over the static seam area. Then, it treats all pixels within the seam area as graph nodes. The graph is directed from the bottom to the top in such a way that each pixel points to the three adjacent ones above (left and right-most pixels only point to the two available). Each of these edge's weight are calculated by using a custom function that compares the absolute color difference between the corresponding pixel in each of the two frames we are trying to stitch. The weight function also checks the foreground masks from the BGS module to see if any player is in the pixel, and if so it adds a large weight to the node. In effect, both these steps will make edges between nodes where the colors differs and players are present have much larger weights. We then run the Dijkstra graph algorithm on the graph to create a minimal cost route from the start of the offset at the bottom of the image to the end at the top. Since our path is directed upwards, we can only move up or diagonally from each node, and we will only get one node per horizontal position. By looping through the path, we therefore get our new cut offsets by adding the node's horizontal position to the base offset.

An illustration of how the final seam looks can be seen in bottom image in figure 8, where the seams without and with color correction are shown in the embedded thumbnails. Timings for the dynamic stitching module can be seen in figure 9. The CPU version is currently slightly faster than our GPU version (as searches and branches often are more efficient on traditional CPUs), but further optimization of the CUDA code will likely improve this GPU performance. Note that the min and max numbers for the GPU are skewed by frames dropping (no processing), and the initial run being slower.

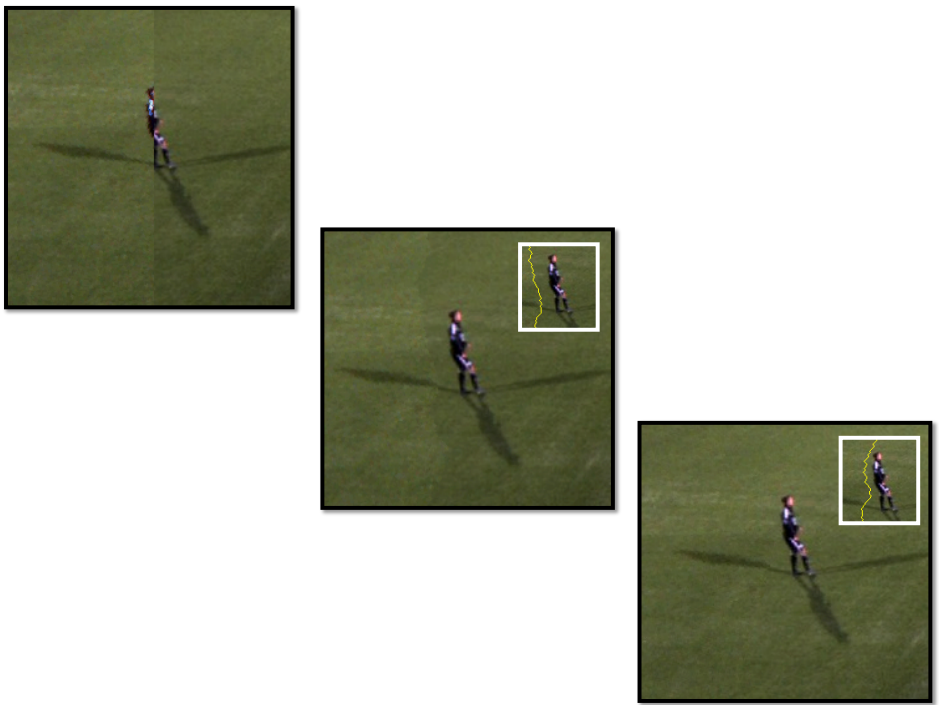


Figure 8. Stitcher comparison - improving the visual quality with dynamic seams and color correction. The first image shows the original stitch [11] with a fixed cut stitch with a straight vertical seam. The middle image shows a dynamic stitch with no color correction. The embedded thumbnail shows the seam. The bottom image shows a dynamic stitch with color correction, i.e., resulting in that the seam is no longer visible.

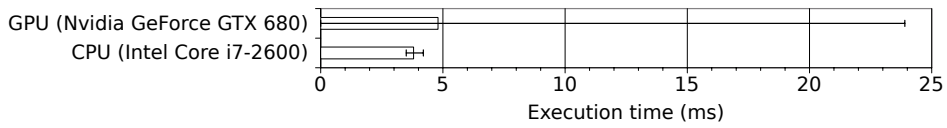


Figure 9. Execution time for dynamic stitching.

4.11. *The YuvConverter module*

Before storing the stitched panorama frames, we need to convert back from RGBA to YUV 4:2:0 for the H.264 encoder, just as in the SingleCamWriter module. However, due to the size of the output panorama, this conversion is not fast enough on the CPU, even with the highly optimize *swscale*. This module is therefore implemented on the GPU. In figure 10, we can see the performance of the CPU based implementation versus the optimized GPU based version.

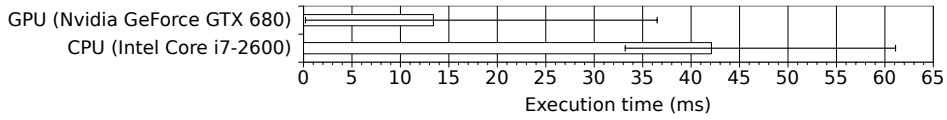


Figure 10. Execution time for RGBA to YUV 4:2:0 conversion.

Nvidia NPP contains several conversion primitives, but not a direct conversion from RGBA to YUV 4:2:0. The GPU based version is therefore first using NPP to convert from RGBA to YUV 4:4:4, and then a self written CUDA code to convert from YUV 4:4:4 to YUV 4:2:0.

4.12. *The Downloader module*

Before we can write the stitched panorama frames to disk, we need to transfer it back to the CPU, which is done by the Downloader module. It runs as a single CPU thread that copies a frame synchronously to the CPU. We could have implemented the Downloader as an asynchronous transfer with double buffering like the Uploader, but since the performance as seen in figure 11 is very good, this is left as future work.

4.13. *The PanoramaWriter module*

The last module, executing on the CPU, is the Writer that writes the panorama frames to disk. The conversion from RGBA to YUV has already been done on the GPU, so the only steps the PanoramaWriter needs to follow, is to first encode the input frame to H.264, and then write the result to disk as three second H.264 video files.

4.14. *Pipeline performance*

In order to evaluate the performance of our pipeline, we used an off-the-shelf PC with an Intel Core i7-3930K processor and an nVidia GeForce GTX 680 GPU. We have benchmarked each individual component and the pipeline as a whole capturing, processing and storing 1000 frames from the cameras.

In the initial pipeline [11], the main bottleneck was the panorama creation (warping and stitching). This operation alone used *974 ms per frame*. As shown by the breakdown into individual components' performance in figure 11, the new pipeline has been greatly improved. Note that all individual components run in real-time running concurrently on the same set of hardware. Adding all these, however, gives times far larger than 33 ms. The reason why the pipeline is still running in real-time is because several frames are processed in parallel. Note here that all CUDA kernels are executing at the same time on a single GPU, so the performance of all GPU modules are affected by the performance of the other GPU modules. On earlier

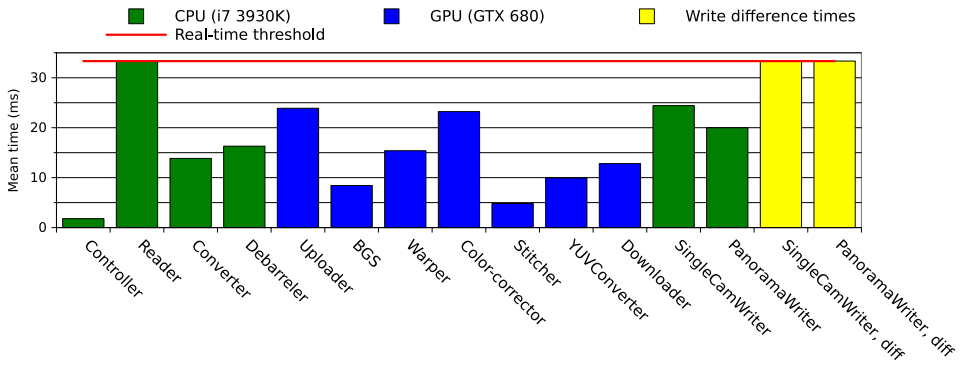
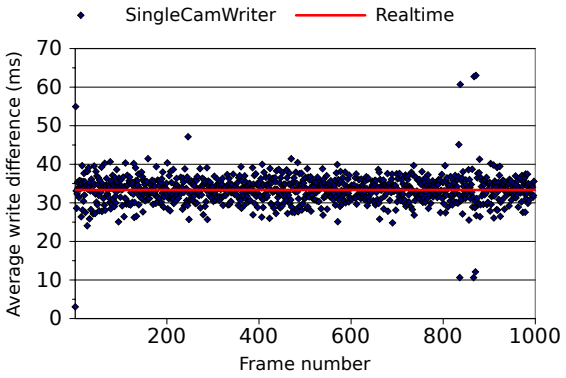


Figure 11. Improved stitching pipeline performance, module overview (Nvidia GeForce GTX 680 and Intel Core i7-3930K)

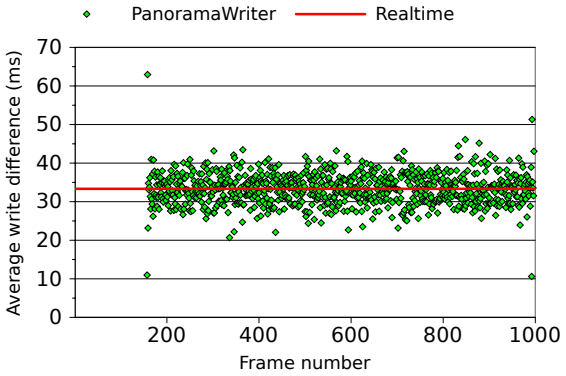
GPUs like the GTX 280, this was not allowed, but concurrent CUDA kernel execution was introduced in the Fermi architecture [24] (GTX 480 and above). Thus, since the Controller module schedules the other modules according to the input rate of 30 fps, the amount of resources are sufficient for real-time execution.

For the pipeline to be real-time, the output rate should follow the input rate, i.e., deliver all output frames (both 4 single camera and 1 panorama) at 30 fps. Thus, to give an idea of how often a frame is written to file, figure 12 shows individual and average frame inter-departure rates. The figures show the time difference between consecutive writes for the generated panorama as well as for the individual camera streams. Operating system calls, interrupts and disk accesses will most likely cause small spikes in the write times (as seen in the scatter plot in figure 12(a) and 12(b)), but as long as the average times are equal to the real-time threshold, the pipeline can be considered real-time. As we can see in figures 11, 12(c) and 12(d), the average frame inter-arrival time (Reader) is equal to the average frame inter-departure time (both SingleCamWriter and PanoramaWriter). This is also the case testing other CPU frequencies and number of available cores. Thus, the pipeline runs in real-time.

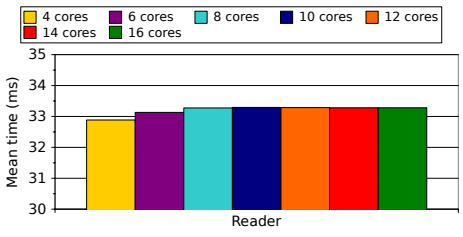
As said above and seen in figure 12(a) and 12(b), there is a small latency in the panorama pipeline compared to writing the single cameras immediately. The total panorama pipeline latency, i.e. the end to end frame delay from read from the camera until written to disk, is equal to 33 ms per sequential module (as long as the modules perform fast enough) plus a 5 second input buffer (the input buffer is because the sensor system has at least 3 second latency before the data is ready for use, and we have added a 2 second buffer for GPU processing). The 33 ms are caused by the camera frame rate of 30 fps, meaning that even though a module may finish before the threshold, the Controller will make it wait until the next set of frames arrive before it is signaled to re-execute. This means that the pipeline latency is 5.33 seconds per frame on average.



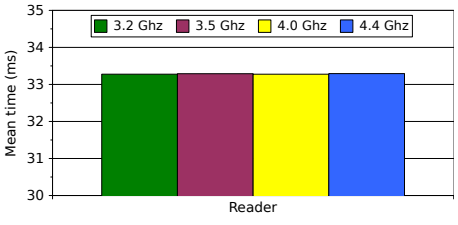
(a) SingleCamWriter inter-departure time



(b) Inter-departure time of PanoramaWriter. The inter-departure frames delayed by five seconds due to the two second safety buffer in CPU/GPU transfer and the three second delay of the sensor data.



(c) Core count scalability.



(d) Core frequency scalability.

Figure 12. Inter-departure time of frames when running the entire pipeline. In a real-time scenario, the output rate should follow the input rate (given here by the trigger box) at 30 fps (33ms).

5. Discussion

Our soccer analysis application integrates a sensor system, soccer analytics annotations and video processing of a video camera array. There already exist several

components that can be used, and we have investigated several alternatives in our research. Our first prototype aimed at full integration at the system level, rather than being optimized for performance. In this paper, however, our challenge has been of an order of magnitude harder by making the system run in real-time on low-cost, off-the-shelf hardware.

The new real-time capability also enables future enhancements with respect to functionality. For example, several systems have already shown the ability to serve available panorama video to the masses [13, 23], and by also generating the panorama video live, the audience can mark and follow particular players and events. Furthermore, ongoing work also include machine learning of sensor and video data to extract player and team statistics for evaluation of physical and tactical performance. We can also use this information to make video playlists [15] automatically giving a video summary of extracted events. Due to limited availability of resources, we have not been able to test our system with more cameras or higher resolution cameras. However, to still get an impression of the scalability capabilities of our pipeline, we have performed several benchmarks changing the number of available cores, the processor clock frequency and GPUs with different architecture and compute resources. Figure 13[a] shows the results changing the number of available cores that can process the many concurrent threads in the CPU-part of pipeline (figure 12(c) shows that the pipeline is still in real-time). As we can observe from the figure, every component runs in real-time using more than 4 cores, and the pipeline as a whole using 8 or more cores. Furthermore, the CPU pipeline contains a large, but configurable number of threads (86 in the current setup), and due to the many threads of the embarrassingly parallel workload, the pipeline seems to scale well with the number of available cores.

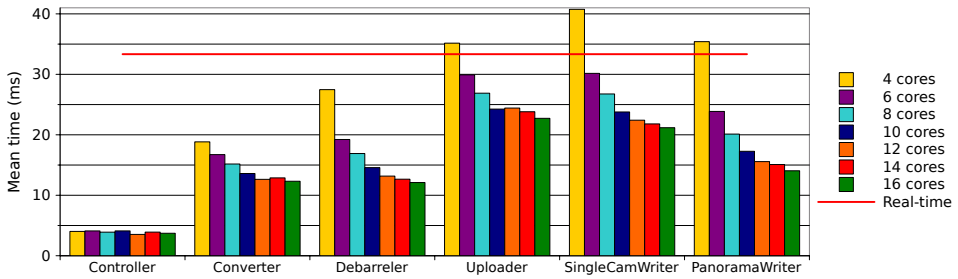


Figure 13. Core count scalability

Similar conclusions can be drawn from figure 14 where the processing time is reduced with a higher processor clock frequency, i.e., the pipeline runs in real-

[a]Note that this experiment was run on a machine with more available cores (16), each at a lower clock frequency (2.0 GHz) compared to the machine installed at the stadium which was used for all other tests.

time already at 3.2 GHz, and there is almost a linear scaling with CPU frequency (figure 12(d) shows that the pipeline is still in real-time). Especially the H.264 encoder scales very good when scaling the CPU frequency. With respect to the GPU-part of the pipeline, figure 15 plots the processing times using different GPUs.

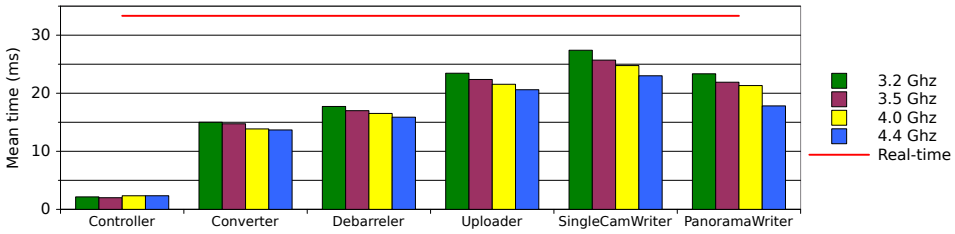


Figure 14. CPU frequency scalability

The high-end GPUs GTX 480 and above (Compute 2.x and higher) all achieve real-time performance on the current setup. The GTX 280 is only compute 1.3 which does not support the concurrent CUDA kernel execution in the Fermi architecture [24], and the performance is therefore slower than real-time. As expected, more powerful GPUs reduce the processing time. For now, one GPU fulfills our real-time requirement, we did therefore not experiment with multiple GPUs, but the GPU processing power can easily be increased by adding multiple cards. Thus, based on these results, we believe that our pipeline easily can be scaled up to both higher numbers of cameras and higher resolution cameras.

6. Conclusions

In this paper, we have presented a prototype of a real-time panorama video processing system. The panorama prototype is used as a sub-component in a real sport analysis system where the target is automatic processing and retrieval of events at a sports arena. We have described the pipeline in detail, where we use both the CPU and a GPU for offloading. Furthermore, we have provided experimental results which prove the real-time properties of the pipeline on a low-cost 6-core machine with a commodity GPU, both for each component and the combination of the different components forming the entire pipeline.

The entire system is under constant development, and new functionality is added all the time, e.g., camera-array-wide synchronized automatic exposure [8], interactive zoom and panning [9, 10], extended search functionality [22] and scaling the panorama system up to a higher number of cameras and to higher resolution cameras [9]. So far, the pipeline scales nicely with the CPU frequencies, number of cores and GPU resources. We plan to use PCI Express-based interconnect technology from Dolphin Interconnect Solutions for low latency and fast data transfers between machines. Experimental results in this respect is though ongoing work and

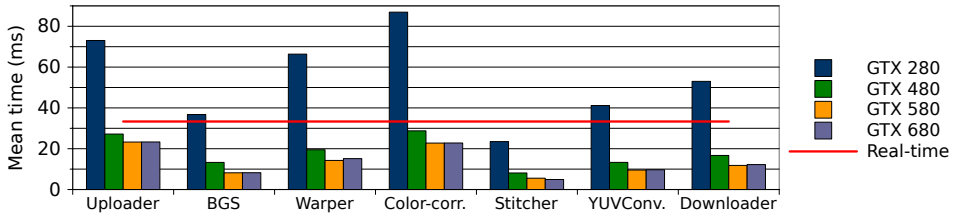


Figure 15. GPU comparison

out of scope in this paper.

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