Reducing Memory Requirements in a Multimedia Streaming Application

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Abstract — This paper investigates memory management for real-time multimedia applications running on resource-constrained electronic devices. The target applications are comprised of a data-driven task chain with a time-driven head and tail and a bounded end-to-end latency. The necessary buffer capacities along the task chain are derived. Subsequently it is shown how a shared memory pool can reduce the total memory requirements of the whole application. The impact of a shared memory pool is also evaluated in the context of scalable applications. The general technique targeted at memory-constrained streaming systems is demonstrated with a video encoding example, showing memory savings of about 19%.

Index Terms — memory management, multimedia systems, streaming applications, reducing memory requirements, buffer capacities, variable execution time.

I. INTRODUCTION

Multimedia applications are known to be data intensive. Many of these applications, especially in the consumer electronics domain, are implemented on resource-constrained embedded systems where the memory space is scarce [1], [2], [3]. Reducing the memory requirements of these applications is therefore very important.

We consider multimedia streaming applications which are implemented as a chain of data-driven tasks communicating via bounded buffers, with a time-driven (i.e. periodic) head and tail task. Fig. 1 shows an example of such an application. Task execution is determined by task priorities, data availability, buffer sizes and time triggering at the boundaries of the system. Let the first and last task in the chain be periodic with period T. The execution times of tasks may vary depending on the data they process, however, we assume that the end-to-end latency for processing a window of M consecutive frames is (strictly) bounded by MT.

In this paper we analyze the execution of a surveillance system, consisting of a video digitizer at the head, a video renderer at the tail, and a number of data-driven tasks. The data-driven tasks have the role of improving the video frames received from the video digitizer through additional processing.

We address the problem of how large the buffers must be and how we must choose the task priorities, in order to meet the real-time constraints.

Contributions

In Section IV we show that, in case of varying execution times, meeting the real-time constraints of the last task in the chain requires a particular priority assignment, and the first and last buffers in the chain to have capacity for M and M+1 frames, respectively, with all other buffers having capacity for 1 frame. We also observe that in the above scenario the number of frames in transit never exceeds M + 1.

In Section V we introduce the concept of a shared memory pool, which encapsulates the memory shared between all buffers in an application. We show how a shared memory pool in an application consisting of a chain of N tasks can save memory for storing M+1+3 frames, for N ≫ 3. To be more precise, since at different stages of the task chain frames may have different sizes, we can save memory for storing M+N−3 smallest frames. Memory is managed in terms of fixed-sized blocks, which simplifies the reallocation of memory between buffers, allowing for an efficient implementation of a shared memory pool.

In Section VI we combine shared memory pools with our earlier work on scalable applications [4] and discuss how they affect the memory requirements of applications in different modes, and how they can reduce the mode change latency.

In Section VII we evaluate the memory savings in a real application and show experimental results for a H.264 video encoder.

II. RELATED WORK

Optimizing memory usage in resource-constrained devices is ever so important with the increasing number of mobile and...
multimedia applications [1], [3], [5]. Yim et al. [1] present an approach for reducing the internal memory fragmentation in flash memory for mobile devices. Ahn et al. [3] consider memory-constrained portable media players and propose a memory allocation scheme for multimedia stream buffers, which allows reducing the number of page faults in heap and thus helps multimedia players perform with a consistent quality. Kim et al. [5] propose a region reuse technique, based on storing objects in upper local regions to the disk and reusing the reclaimed space for new object allocations, and hence reducing heap memory usage in mobile consumer devices with very limited memory. In contrast to [1], [3], [5] which try to manage the memory requirements dictated by the applications, in this paper we focus on actually reducing the memory requirements.

Albu [6] explores how the assignment of task priorities and buffer capacities impact the behavior of multimedia streaming applications comprised of a task chain. The author shows that a task chain with a time-driven tail exhibiting varying task execution times (where processing a window of \( M \) consecutive frames is bounded by \( MT \) ) will meet its real-time constraints if the last buffer has capacity for \( M \) frames. They also show that a task chain with a time-driven head and tail, and \( M = 2 \), will meet its real-time constraints if all buffers have capacity 1. In this paper we derive the buffer capacities for a chain consisting of a time-driven head and tail and an arbitrary \( M \).

Goddard 0 studies the real-time properties of PGM dataflow graphs, which closely resemble our media processing graphs. Given a periodic input and the dataflow attributes of the graph, exact node execution rates are determined for all nodes. The periodic tasks corresponding to each node are then scheduled using a preemptive Earliest Deadline First algorithm. For this implementation of the graph, the author shows how to bound the response time of the graph and the buffer requirements. However, it is limited to task sets with deadlines equal to the period, i.e. without self-interference. This approach provided valuable insights, but no rigorous support for analyzing and steering system behavior and associated resource needs has resulted.

Though we consider variations in execution time, we do not consider overload problems resulting from the inability to process the input in time. Approaches aiming at that situation can be used to prevent this from happening [7], [8], or to deal with it when it happens, through scaling or skipping the media content [9], [8], [10].

In [4] we investigated scalable applications, which can operate in one of several predefined modes, where each mode specifies the resource requirements in terms of \( M \) for all the buffers belonging to the application. We showed how to use in-buffer scaling to reduce the memory requirements of each buffer. Upon a mode change request for a mode with a smaller \( M \) and smaller memory requirements, we would drop the least significant frames from the chain and/or reduce the number of blocks for certain frames, and show how this could reduce the mode change latency. In this paper we concentrate on how a shared memory pool will affect the memory requirements of a scalable application in different modes.

III. System Model

Below we describe our application and platform models.

A. Application model

An application consists of a chain of \( N \) tasks \( \tau_1, \ldots, \tau_N \) communicating via \( N-1 \) shared buffers. Each task \( \tau_i \) is assigned a fixed and unique priority \( P(\tau_i) \), with \( P(\tau_i) < P(\tau_j) \), meaning that \( \tau_i \) has a higher priority than \( \tau_j \). The first and the last tasks in the chain are time driven, with periods \( T_1 \) and \( T_N \), phasings \( \varphi_1 \) and \( \varphi_N \), and relative deadlines \( D_1 \) and \( D_N \) respectively. The time between activations and deadlines represent the times that the application may access the input frame buffer and the output frame buffer respectively. All other tasks in the chain are data driven.

Clearly, the periods of the head and tail tasks must be consistent with the frame counts since this system can only be expected to work if the inflow equals the outflow. In this paper we do not consider variations in the number of frames produced or consumed by a task nor any other data dependent behavior than varying computation times. Therefore we adopt

\[
T_1 = T_N = T.
\] (1)

Let \( E^k_i \) be the execution time needed by task \( \tau_i \) to process the \( k \)’th frame, and \( E_i = \max_k E^k_i \) be the worst-case execution time of task \( \tau_i \) on any frame. We use \( \tau_{l,j} \) to denote a sub-chain of tasks \( \tau_k, \ i \leq k \leq j \). Let \( E_{l,j}^k = \sum_{i=l}^{j} E_i^k \) be the execution time needed by chain \( \tau_{l,j} \) to process the \( k \)’th frame.

Buffers represent FIFO queues, which are used to communicate data between tasks. They are responsible for the majority of memory requirements of an application. Each buffer \( q \) has a finite initial capacity \( \text{Cap}(q) \), defining the maximum number of frames which can be stored in the buffer.

Each buffer \( q \) provides a read interface comprised of methods read_acquire(\( q \), frame) and read_release(\( q \), frame), and a write interface comprised of methods write_acquire(\( q \), frame) and write_release(\( q \), frame). These interfaces provide a hand-shake protocol allowing to do in-memory processing. A call of read_acquire(\( q \), frame) will remove a full element from \( q \) and leave a reference to that element in frame; a call of read_release(\( q \), frame) will add the element referred to by frame to \( q \) as an empty slot. The semantics of write_release and write_acquire are symmetric. The acquire operations are blocking if no full, resp. empty frames are available.

The pseudo code for a data-driven task is shown in Fig. 2. In each iteration, task \( \tau_i \) reads a frame from \( q_{i-1} \) using read_acquire(\( q_{i-1} \), inFrame) and retrieves a reference to a buffer slot inside \( q_i \) using write_acquire(\( q_i \), outFrame). While processing the input frame from \( q_{i-1} \) it writes the
output frame to the slot it obtained from \( q_i \). After it has finished processing the frame, it releases the input frame by calling \texttt{read\_release}(q_{i-1},\ inFrame)\) and marks the output frame as ready for reading by calling \texttt{write\_release}(q_i, outFrame).

**Task \( \tau_i \):**

\[
\text{[ \[ \text{var inFrame, outFrame: Frame reference; } \\
\text{while (true) \{ } \\
\text{ write\_acquire(q_i, outFrame). } \\
\text{ read\_acquire(q_{i-1}, inFrame); } \\
\text{ process([inFrame, outFrame]; } \\
\text{ read\_release(q_{i-1}, inFrame); } \\
\text{ write\_release(q_i, outFrame); } \\
\text{ \}} \]
\]}

*Fig. 2. Pseudo-code for a data-driven task.*

The head task has no input buffer and the tail task has no output buffer. Moreover, the head and tail task are time driven, as outlined in Fig. 3 and Fig. 4. Note that a time-driven task can block on both communication and time.

**global inputFrameBuffer: Frame reference;**

**Task \( \tau_1 \):**

\[
\text{[ \[ \text{var outFrame: Frame reference; } \\
\text{ k: Integer; } \\
\text{ k := 0; delay\_until(q_1); } \\
\text{ while (true) \{ } \\
\text{ write\_acquire(q_1, outFrame); } \\
\text{ process1(inputFrameBuffer, outFrame); } \\
\text{ write\_release(q_1, outFrame); } \\
\text{ k := k + 1; delay\_until(q_1 + kT_1); } \\
\text{ \}} \]
\]}

*Fig. 3. Pseudo-code for a time-driven head task \( \tau_1 \).*

**global displayBuffer: Frame reference;**

**Task \( \tau_N \):**

\[
\text{[ \[ \text{var inFrame: Frame reference; } \\
\text{ k: Integer; } \\
\text{ k := 0; delay\_until(q_N); } \\
\text{ while (true) \{ } \\
\text{ read\_acquire(q_{N-1}, inFrame); } \\
\text{ processN(inFrame, displayBuffer); } \\
\text{ read\_release(q_{N-1}, inFrame); } \\
\text{ k := k + 1; delay\_until(q_N + kT_N); } \\
\text{ \}} \]
\]}

*Fig. 4. Pseudo-code for a time-driven tail task \( \tau_N \).*

Note that \texttt{inputFrameBuffer} and \texttt{displayBuffer} represent references to memory which is external to the task chain. \texttt{process}_1 and \texttt{process}_N will simply copy frames to and from the local buffers \( q_i \) and \( q_{N-1} \), respectively.

**B. Real-time constraints**

The application expresses its real-time requirements in terms of relative deadlines \( D_1 \) on task \( \tau_1 \) and \( D_N \) on task \( \tau_N \), with \( E_1 \leq D_1 \leq T \) and \( E_N \leq D_N \leq T \). More precisely, we require that the \( k \)‘th instance of tasks \( \tau_1 \) and \( \tau_N \) (processing the \( k \)‘th frame) execute within time intervals \([\varphi_1 + kT_1, \varphi_1 + kT_1 + D_1]\) and \([\varphi_N + kT_1, \varphi_N + kT_1 + D_N]\), respectively.

**C. Platform model**

We assume a single processor. Furthermore, we assume that memory is managed in terms of fixed-sized blocks. Each frame may span across several memory blocks, but each block contains data belonging to at most one frame. At different stages of the task chain, frames may have different sizes (e.g. raw video frames are likely to be larger than the encoded frames).

A buffer expresses its memory requirements in terms of memory reservations (or memory budgets) [4], where each reservation guarantees access to the requested number of blocks. Memory reservations are granted only if there is enough space in the system-wide memory pool, and memory allocations are granted only if there is enough space within the corresponding reservation.

Several buffers may request memory from the same reservation, giving rise to a shared memory pool. The memory pool guarantees that the cumulative requirement of all buffers using it does not exceed its capacity.

**IV. Time-driven Head and Tail Tasks**

Because of the equal periods of the head and tail tasks, and the assumption that each instance of a task consumes and produces exactly one frame (and the worst-case execution time for processing one frame is within \( T \)), there are a constant number of frames in transit within the system. Clearly, if the worst-case execution time for processing one frame is within \( T \) the system will satisfy the real-time constraints with just 1 frame in transit.

However, this strict restriction on the execution time of the complete chain is not realistic. We would like to allow the processing time for individual frames to take longer than \( T \), as long as the processing of other frames will compensate for it.

**A. Task priorities**

When the computation time of a frame is larger than \( T \), more that one frame will be in transit. Then, the priority assignment becomes important.
According to (2), the chain is guaranteed to reach idle state when the head task has written the frame to the first buffer, the higher priority data-driven tasks preempt \( \tau_1 \) which then has to wait until they complete.

**Example 1:** Consider the system of Fig. 5 with three tasks where the head task has the lowest priority. If the execution time of a frame exceeds \( D_1 = T \) then the head task will miss the deadline of the next frame as the head task will not be scheduled before a computation has been completed. A similar remark holds for the tail task from which we conclude that the head and tail tasks should have a higher priority than the middle tasks.

We use \( S^k \) to denote the execution time needed to produce the \( k \)th frame, after producing the \( k-1 \)th frame. We allow \( S^k \) to vary, but the duration of each size \( M \) window has to be smaller than \( MT \), i.e.

\[
\sum_{i=k-M+1}^{k} S^i < MT, \quad k \geq M.
\]  

(2)

Here \( M \) is a natural number, which can be regarded as a system parameter. The strict “smaller than” relation indicates that there will always be some idle time in the processing of any sequence of \( M \) frames.

Now, consider the system at time \( 0 \) when \( \tau_1 \) starts and suppose \( \tau_N \) does not execute. Then, according to (2), after \( MT \) time units, the last buffer will contain \( M \) frames. We start \( \tau_N \) shortly after \( MT \) and choose \( E_N = MT + D_1 \) (with \( E_1 \leq D_1 \leq T - E_N \)), making sure that, if we assign \( \tau_N \) a lower priority than \( \tau_1 \), \( \tau_N \) will not be preempted by \( \tau_1 \). From this point on the number of frames in transit within the chain is either \( M \) or \( M+1 \), as long as \( \tau_1 \) does not block on output and \( \tau_N \) does not block on input.

By the time \( E_N = MT + D_1 \), the chain \( \tau_{1,N-1} \) will have done work equal to

\[
\sum_{i=1}^{M} E_{i,N-1}^i .
\]  

(3)

During the time interval \( [E_N, E_N + MT) \) the chain will produce \( M \) frames and will execute for

\[
\sum_{i=1}^{M} S^i = \sum_{i=M+1}^{2M} E_{i,N-1}^i + \sum_{i=M+1}^{E_N} E_N^i .
\]  

(4)

According to (2), the chain is guaranteed to reach idle state within \( MT \) time units. At that time all of the \( M \) or \( M+1 \) frames in transit will be residing in \( q_{N-1} \). In general, processing a window of size \( M \) preceding the production of frame \( k \), after frame \( k-1 \), will require

\[
\sum_{i=k-M+1}^{k} S^i = \sum_{i=k-M+1}^{k-M} E_{i,N-1}^i + \sum_{i=k-M+1}^{E_N} E_N^i .
\]  

(5)

Note that the contribution of \( \tau_{1,N-1} \) and \( \tau_N \) are of different iterations of the tasks (corresponding to different frames). Since the head and tail tasks in a multimedia streaming application will usually simply copy frames from or to an external buffer, we can bound their contribution from above and take their worst-case execution times \( E_N \) and \( E_N \).

The previous example suggests that the head and tail tasks should be assigned priorities higher than any of the data-driven tasks in between. With these choices we can regard the system as consisting of three parts: high priority \( \tau_1 \), low priority data-driven chain \( \tau_{2,N-1} \) and high priority \( \tau_N \).

Let \( P(\tau_1) \) be maximal, \( P(\tau_2) \) be minimal, \( P(\tau_N) = P(\tau_1) + 1 \), and \( P(\tau_{N-1}) = P(\tau_2) - 1 \). Since tasks \( \tau_1 \) and \( \tau_N \) are time-driven and have priorities higher than any data-driven task in the chain, they can interrupt the execution of the chain at arbitrary places. However, since priorities \( P(\tau_2) \) and \( P(\tau_{N-1}) \) are lower than the priorities of all other tasks in the chain \( \tau_{2,N-1} \), tasks \( \tau_1 \) and \( \tau_N \) will not affect the execution order of actions in \( \tau_{2,N-1} \).

**B. Capacity of the first and last buffer**

The following examples demonstrate how this particular priority assignment affects the required buffer capacities.

**Example 2:** Let us assume the above priority assignment and the following scenario. Task \( \tau_1 \) writes a frame to \( q_1 \). Subsequently \( \tau_2 \) reads it from \( q_1 \) and processes it. Let the frame be computationally intensive. Since \( P(\tau_2) \) is minimal, the data-driven chain \( \tau_{2,N-1} \) will process each new frame completely to \( q_{N-1} \) before \( \tau_2 \) occurs again. According to (2) the data-driven chain may be busy with processing the frame for at most \( MT \) time units. During that time the time-driven \( \tau_1 \), which has the highest priority, will have written \( M \) frames to \( q_1 \).

**Example 3:** Continuing with the last example, let us consider the capacity of the last buffer in the chain. Equation (2) implies that after \( MT \) time units the data-driven chain will process the frames in no time, since execution time for processing any window of size \( M \) is bounded by \( MT \). Therefore, the data-driven chain \( \tau_{2,N-1} \) will process the next \( M \) frames before the \( \tau_1 \) writes another frame into \( q_1 \), essentially purging the first buffer. Since the head and tail tasks share the same period, these \( M \) frames will accumulate in \( q_{N-1} \).
Assume that shortly after, the next frame which enters the chain is very easy to process, i.e. that $\tau_{2,N-1}$ will push this frame through to $q_{N-1}$ before $\tau_N$ gets a chance to remove a frame from $q_{N-1}$. At this point $q_{N-1}$ will contain $M+1$ frames. However, since tasks $\tau_1$ and $\tau_N$ share the same period $T$, the following frame will not arrive before $\tau_N$ had the chance to remove a frame from $q_{N-1}$. The last buffer will therefore never exceed $M+1$ frames.

The previous two examples imply that the buffer capacities should be $Cap(q_i) = M$ and $Cap(q_{N-1}) = M+1$.

C. Capacity of the middle buffers

In the previous examples we made no assumption on the capacities of the middle buffers, i.e. buffers $q_i$ for $2 \leq i \leq N-2$. Now we show that all middle buffers can have capacity 1 by showing that $\tau_{2,N-1}$ will never become blocked on communication whenever there is work pending, or in other words, by showing that none of the tasks in $\tau_{2,N-1}$ will block on output.

Let us consider the situation at time $\varphi_N = MT + D_1$. During the initial $MT$ time units, task $\tau_1$ will have inserted $M$ frames into the chain. According to (2), by the time $\varphi_N$ the $M$ frames have been pushed to the last buffer $q_{N-1}$. We need to show that none of the tasks in $\tau_{2,N-1}$ will block on a full buffer while there is still work pending. Assume that at time $MT$, i.e. before $\tau_N$ had a chance to remove a frame from $q_{N-1}$, a new frame arrives which is very easy to process. The chain $\tau_{2,N-1}$ will immediately push this frame through to $q_{N-1}$, which at this point will reach $M+1$ frames. However, since tasks $\tau_1$ and $\tau_N$ share the same period $T$, the next frame will not arrive before $\tau_N$ had the chance to remove a frame from $q_{N-1}$. Since $Cap(q_{N-1}) = M+1$, task $\tau_{N-1}$ cannot become blocked on $q_{N-1}$. Moreover, since $P(\tau_2)$ is minimal, $\tau_{2,N-1}$ will process each new frame completely to $q_{N-1}$ before $\tau_2$ occurs again. Hence none of the buffers within the chain $\tau_{2,N-1}$ will exceed their capacity of 1, and consequently none of the tasks in $\tau_{2,N-1}$ will ever block when there is work pending.

D. Meeting real-time constraints

Since the head and tail tasks are activated periodically, if we show that $\tau_1$ will never block on output and $\tau_N$ will never block on input, than we will have shown that the tasks $\tau_1$ and $\tau_N$ will meet their real-time constraints. We demonstrate that this blocking of $\tau_1$ or $\tau_N$ cannot occur, by showing that $q_1$ can never be full and $q_{N-1}$ can never be empty. We show it by contraposition.

Assume that blocking of $\tau_1$ or $\tau_N$ on communication does in fact occur and consider the first blocking of either of the two tasks at time $t$. Since we have assumed a single processor allowing only a single task executing at a time, the two tasks cannot block simultaneously.

This blocking task cannot be $\tau_1$ since, as long as $\tau_N$ does not block, $\tau_{2,N}$ can either process or buffer the frames (given the buffer capacities derived in Sections IV.B and IV.C); hence, the contents of $q_i$ can vary up to $M$ but will reach 0 within each $MT$ time interval.

Then the blocking task must be $\tau_N$, waiting for a new frame. However, as long as $q_{N-1}$ contains less than $M$ frames, the system is not idle as there are frames in transit; because of (2) the state with $q_{N-1}$ containing $M$ frames recurs within at most $MT$ time units again and thus can never reach 0. It follows that no such first moment of blocking exists.

Now that we have shown that $\tau_1$ does not block on output and $\tau_N$ does not block on input, we can state the following theorem.

Theorem 1: Given a single application comprised of a task chain in Fig. 1 with a time-driven head and tail task, executing on a single processor, satisfying (2) and (5), and the following settings:

\begin{itemize}
  \item $P(\tau_1)$ is maximal, $P(\tau_2)$ is minimal
  \item $P(\tau_N) = P(\tau_1) + 1$, $P(\tau_{N-1}) = P(\tau_2) - 1$
  \item $q_i = MT + D_1$
  \item $Cap(q_i) = M$, $Cap(q_{N-1}) = M+1$
\end{itemize}

the real-time constraints of tasks $\tau_1$ and $\tau_N$ will be satisfied, for $3 \leq N$. $E_i = D_i = T - E_N$, $E_N = D_N = T$, and

$$\sum_{i=k-M+1}^{k} S^i < MT, \quad k \geq M .$$

Note that since we made no assumptions on the sizes of buffers $q_i$, $1 < i < N - 1$, they can all have capacity 1.

In this section we have implicitly assumed a single application in the system. In case there are several applications running side by side, we have to increase the lower bound on deadlines $D_i$ and $D_N$, taking the interference of other applications into account.

V. REDUCING MEMORY REQUIREMENTS

From Theorem 1 we know that the total capacity of all buffers in an application consisting of a chain of $3 \leq N$ tasks, as shown in Fig. 1, is equal to $M + (N - 3) + (M + 1)$ frames, where $M$ represents the first buffer, $(N - 3)$ represents the buffers with capacity 1 between the first and last buffer, and $(M + 1)$ represents the last buffer. However, as mentioned in Section IV.A, the total number of frames in transit never exceeds $M + 1$ frames.

Rather than allocating each buffer its required capacity, we can have them share a common memory pool, since all buffers together will never require more memory than for storing $M + 1$ frames. In this way we can save the memory for storing $M + N - 3$ frames, for $3 \leq N$.

At different stages of the task chain frames may have different sizes. Let $S_i$ be the frame requirement for a single
frame at stage \( i \), i.e. the size (in terms of blocks) of the largest frame ever stored in the \( i \)th buffer in the chain. A chain of \( N \) tasks defines a collection of frame requirements:

\[
\left\{ s_1, s_2, \ldots, s_{N-3}, s_{N-2}, s_{N-1}, s_N \right\}
\]

If we order the frame requirements in the application in ascending order of \( s_j \), then using a shared memory pool can save the memory space required by the \( M + N - 3 \) smallest frame requirements. More precisely, if we arrange the \( M + (N - 3) + (M + 1) = 2M + N - 2 \) frame requirements in ascending order in a sequence

\[
\left\{ r_1, r_2, \ldots, r_{2M + N - 2} \right\}
\]

such that

\[
\forall i : 1 \leq i \leq 2M + N - 2 : r_i \leq r_{i+1}
\]

then the absolute memory savings are given by

\[
\sum_{i=1}^{M+N-3} r_i
\]

and the relative memory savings are given by

\[
\frac{\sum_{i=1}^{M+N-3} r_i}{\sum_{i=1}^{2M+N-2} r_i}
\]

The memory reservations based on fixed-sized blocks simplify the reallocation of memory between buffers, allowing for an efficient implementation of a shared memory pool.

VI. MODE CHANGES IN STREAMING APPLICATIONS

In this section we investigate reallocating memory between applications. Let us continue with the multimedia processing application example shown in Fig. 1 and consider a system comprised of two such applications. In the new setting both applications are scalable, meaning that when they are provided more resources they can generate higher quality output. More specifically, given more processing time and more memory, each application will generate a higher quality video encoding. Higher quality video will require more memory for storing the buffered frames, thus increasing the \( s_j \) values. Also, longer processing time will result in greater fluctuations of the latency of the processing chain and consequently larger \( M \), requiring larger buffers along the processing chain.

A scalable application can operate in one of several predefined modes, where each mode specifies the resource requirements in terms of \( M \) and \( s_j \) for all the buffers belonging to the application. In a system comprised of two such applications executing on a memory constrained platform, if we assume that the available memory cannot accommodate both applications at their highest quality at the same time, we may need to reallocate the memory between the applications during runtime to provide a system wide Quality of Service. We refer to such a resource reallocation as a mode change.

A mode change exhibits a mode change latency, defined as the length of the time interval between a mode change request and the time when all resources have been reallocated. In [4] we showed how to use in-buffer scaling to reduce the memory requirements of each buffer. In this section we concentrate on how a shared memory pool will affect the memory requirements of a scalable application in different modes.

Equation (9) indicates that the relative memory savings due to a shared memory pool increase with increasing \( M \), as visualized in Fig. 7.

A higher quality mode (i.e. a mode requiring more resources, in particular more processor time) is likely to exhibit larger variation in execution time of the individual tasks, and hence also of the complete chain, thus increasing \( M \) (provided it is not assigned a larger processor share after the mode change).

Also, (8) and (9) indicate that the smaller the variation in the \( s_j \) the larger the memory savings due to a shared memory pool. Many multimedia streaming applications can be classified as encoders or decoders. An encoder receives a fixed-sized input (e.g. raw video frames from a camera) and encodes it into an output, of which the size depends on the quality settings. Conversely, a decoder will receive a variable sized input and generate a fixed-sized output (e.g. decoded frames rendered to a screen). Given the fixed-sized output or input frames, an application operating in a lower quality mode is likely to exhibit large variation in the frame sizes at different stages of the chain.

In summary, scalable applications are likely to exhibit larger relative memory savings due to a shared memory pool when they execute in higher modes.

Note that if the memory reservations underlying the memory pools of different applications are managed in terms of fixed-sized blocks of the same size, then the reallocation of memory between memory pools belonging to different applications will be simpler and more efficient. Memory blocks can be simply added and removed from a list of available blocks, compared to a solution based on finding the best fit between memory requirements and available blocks. Moreover, rather than scaling the memory reservations for all buffers one by one, a shared memory pool allows to scale the memory requirements of the complete chain in a single step. Thus a shared memory pool, next to reducing the memory requirements of a scalable application, can also reduce the mode change latency.

VII. RESULTS

Fig. 6 shows an application example of a H.264 video encoder [11], which is commonly used in the consumer electronics domain. We used it to evaluate the memory savings in a real application.

\footnote{The data residing in the buffers still needs to be scaled for each buffer individually.}
The application consists of three tasks: the video digitizer provides raw frames in CIF format (with resolution 352x288 pixels) for the H.264 video encoder, which produces a 300kbs video stream with the same resolution for the video renderer. The $s_1$ parameter is equal to the size of a raw input frame, i.e. $s_1 = 352 \times 288 = 101376$ bytes. We have measured the largest frame ever produced by the H.264 encoder for a series of video sequences\footnote{Available at http://media.xiph.org/video/derf/} to be $s_2 = 26002$ bytes. By using a shared memory pool, in our chain of $N = 3$ tasks we can save the memory for storing $M + N - 3 = M$ of the smaller frames, which in this case are the encoded frames of size $s_2$. The relative memory savings are therefore given by

$$\frac{M \times s_2}{M \times s_1 + (M + 1) s_2}.$$ \hfill (10)

Fig. 7 shows the relative memory savings of our approach as a function of $M$, by filling in the above values for $s_1$ and $s_2$ in (10).

\begin{figure}
\centering
\includegraphics[width=0.8\textwidth]{fig7}
\caption{Memory savings in our example application as a function of $M$.}
\end{figure}

\begin{figure}
\centering
\includegraphics[width=0.8\textwidth]{fig8}
\caption{Memory savings for different ratios between $s_1$ and $s_2$, assuming $N = 3$ and $M = 4$.}
\end{figure}

VIII. CONCLUSIONS

We have shown a general mechanism for reducing memory requirements in a streaming application comprised of a chain of tasks with periodic head and tail tasks communicating via shared buffers. The proposed method is based on having the buffers share a common memory pool. We have shown that the total capacity of all buffers in an application consisting of a chain of $N = 3$ tasks is equal to $M + (N - 3) + (M + 1)$ frames. We exploit the fact that in the above scenario the total number of frames in transit never exceeds $M + 1$, and propose to share a memory pool with capacity for $M + 1$ frames between all the buffers. As a result, in an application consisting of a chain of $N$ tasks, we can save memory for storing $M + N - 3$ frames. To be more precise, since at different stages of the task chain frames may have different sizes, we can save memory for storing $M + N - 3$ smallest frames.

Managing the memory in terms of fixed-sized blocks will simplify the reallocation of memory between buffers, allowing for an efficient implementation of a shared memory pool. If applied to scalable applications, a shared memory pool will result in greater relative memory savings for applications operating in higher modes.

The results for an H.264 encoder show memory savings of around 19\%. The approach is targeted at resource-constrained systems, such as those found in consumer electronics.

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REFERENCES


BIOGRAPHIES

Mike Holenderski is a Ph.D. student at the Eindhoven University of Technology, the Netherlands. He received his B.Sc. in 2003 and M.Sc. (with honors) in 2007, both from the Eindhoven University of Technology. His main research interests are in the area of reservation-based multi-resource scheduling in embedded real-time systems.

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Johan Lukkien is head of the System Architecture and Networking Research group at Eindhoven University of Technology since 2002. He received M.Sc. and Ph.D. from Groningen University in the Netherlands. In 1991 he joined Eindhoven University after a two years leave at the California Institute of Technology. His research interests include the design and performance analysis of parallel and distributed systems. Until 2000 he was involved in large-scale simulations in physics and chemistry. Since 2000, his research focus has shifted to the application domain of networked resource-constrained embedded systems. Contributions of the SAN group are in the area of component-based middleware for resource-constrained devices, distributed coordination, Quality of Service in networked systems and schedulability analysis in real-time systems.