CHECKSOFT: A SCALABLE EVENT-DRIVEN SOFTWARE ARCHITECTURE FOR KEEPING TRACK OF PEOPLE AND THINGS IN PEOPLE-CENTRIC SPACES

Rohan Sarkar
School of Electrical and Computer Engineering
Purdue University
West Lafayette, IN 47907
sarkarr@purdue.edu

Avinash C. Kak
School of Electrical and Computer Engineering
Purdue University
West Lafayette, IN 47907
kak@purdue.edu

February 23, 2021

ABSTRACT

We present CheckSoft, a scalable event-driven software architecture for keeping track of people-object interactions in people-centric applications such as airport checkpoint security areas, automated retail stores, smart libraries, and so on. The architecture works off the video data generated in real time by a network of surveillance cameras. Although there are many different aspects to automating these applications, the most difficult part of the overall problem is keeping track of the interactions between the people and the objects. CheckSoft uses finite-state-machine (FSM) based logic for keeping track of such interactions which allows the system to quickly reject any false detections of the interactions by the video cameras. CheckSoft is easily scalable since the architecture is based on multi-processing in which a separate process is assigned to each human and to each “storage container” for the objects. A storage container may be a shelf on which the objects are displayed or a bin in which the objects are stored, depending on the specific application in which CheckSoft is deployed.

Keywords People-centric Systems, Event Driven Architecture, Concurrent Software Architecture, Intelligent Systems, Finite State Machine Automata, Video Surveillance Systems, Airport Checkpoint Security, Automated Retail Stores, Video Analytics and Monitoring

1 Introduction

This paper presents a scalable software architecture for automating video monitoring of people-centric spaces. We must mention at the very outset that the purpose of this paper is not to address the computer vision issues related to detecting people, objects, and their interactions.

On the other hand, our aim in this paper is solely to present an error-tolerant and scalable software design that uses finite-state machine (FSM) logic capable of rejecting false detections reported by the underlying video cameras. As we show in this paper, with FSM the system can quickly catch moment-to-moment discrepancies and inconsistencies in the detections reported by the sensors.

Whereas FSM allows for quick checks on the validity of the detected human-object interactions, the multi-processing design we have used for the architecture allows it to be scalable. Scalability means that the architecture would automatically allow for an arbitrary number of people and objects to be present in the space being monitored with latencies limited only by the computational power of the underlying hardware platform.

With its high-level attributes as described above, a software architecture of the type presented in this paper can be expected to find applications in the new-age retail stores with no sales clerks and cash registers, smart libraries that

---

1 Even though the computer vision aspects of the overall problem are not the focus of this paper, for the sake of validating the software architecture presented here, we will show results using actual and simulated video streams.
allow a customer to simply walk out with the book desired, airport checkpoint security areas where it is important to keep track of the passengers and their belongings, and so on. Additionally, since CheckSoft is capable of recording on a continuous basis the history of people-object interactions in the monitored space, another important application of such a software system is that it lends itself to an easy post-facto analysis of the log files for gaining insights into people’s reaction to the displayed objects. The results of such analysis may be used for a more productive arrangement of the objects vis-a-vis the people.

The application scenarios presented above might cause a reader to think that our work is similar to or overlaps significantly with a rather popular research area: smart (or intelligent) spaces in which wireless sensors attached to the objects and cameras are used to keep track of just the people or just the objects. The goal of the work presented in this paper is different: Keeping track of people-object interactions \(^2\), in the sense that we want our system to track ownership and possession relationships as people interact with the objects, exchange them, leave them behind in monitored spaces when they shouldn’t, and so on.

A generic software architecture for keeping track of people-object interactions should be able to accommodate the fact that the objects may present themselves differently in different applications. For example, in a retail store, the objects are likely to be placed on the shelves where either each object is directly accessible to a customer or, when the objects are stacked, the topmost object is directly accessible. On the other hand, in an airport checkpoint security area, the objects will be the personal belongings that the passengers divest in the bins that are then placed on the conveyor belt. In this case, the objects will be in a heap in the bins or placed directly on the conveyor belt. In the software system presented in this report, we use the notion of storage to address at a generic level these differences between the different applications. For retail store application, an instance of storage could be a shelf containing items. On the other hand, an instance of the same for airport checkpoint security would be a bin in which the passengers divest their belongings.

In addition to the differences in how the objects may present themselves to the system in different applications, a system like ours must also be mindful of the fact that the acceptable rules for people-object interactions may be different in different applications. For example, in an airport checkpoint security application, passengers should be allowed to collect their own items only at the end of the screening process. In a museum, visitors should not be allowed to touch any expensive exhibits, and, in a library, readers should not be allowed to misplace books in wrong shelves at the time of returning the books.

The software architecture we present in this paper meets the challenges described above and is also scalable at the same time. We achieve scalability by using multiprocessing and concurrency. A unique process is associated with each entity, that is with each individual and with each storage unit containing objects in the space being monitored. This decentralizes the bookkeeping for keeping track of the different states of each individual and each storage container — the process assigned to each entity takes care of all such details. The decentralization also eliminates the risk of deadlock that may arise due to contention for the entity state information. The communication between the processes is implemented using Message Passing Interface (MPI).

Here is a summary of the main contributions of this paper:

- CheckSoft can keep track of concurrent person-object interactions involving an arbitrary number of people and also an arbitrary number of objects in a monitored space in real-time using an architecture based on multi-processing and inter-module communications based on message passing. Each significant entity in the system is assigned a separate process. The overall design achieved in this manner eliminates the risk of any deadlocks that may arise due to contention for the entity state information.
- CheckSoft allows for an arbitrary number of video trackers to be plugged into the system on a plug-n-play basis. It is event-driven and can operate asynchronously in real-time vis-a-vis the events detected from the video-feeds of any arbitrary number of video cameras.
- The architecture adheres to the time-honored principles of good object-oriented design and uses finite-state-machine based logic for fault tolerance vis-a-vis any temporal discrepancies in the events detected by the sensors.
- The architecture can be applied to a variety of applications that require tracking the interactions between people and objects by only making minor modifications to the application-specific FSM logic and without any major architectural changes.

CheckSoft was validated with data from actual video cameras. The scalability of CheckSoft was validated with a simulator.

---

\(^2\) By ownership of an object, we mean the first individual identified as possessing the object.
In the rest of this report, we start in Section 2 with a quick review of the literature that has two parts to it: the first part deals with the software engineering literature that has guided the design of CheckSoft, and second part with the literature related to keeping track of people and objects in video monitored spaces. Subsequently, in Section 3 we then introduce the principal data structures of the system for representing the relational information in the system. The definitions presented for these data structures should give the reader a sense of the generality of the software architecture. Finally, the overall system architecture is summarized in Section 4 and presented in details in Section 5. In Section 6, we verify scalability and deadlock-free operation for the proposed architecture. In Section 7, we validate the operation of CheckSoft with actual video trackers and test the scalability and robustness of CheckSoft using a simulator.

2 Literature Review

We will first present the literature that guided our software design in Section 2.1 and then compare related software systems in Section 2.2.

2.1 Literature that Guided Our Software Design

Ning et al. [2] states that the two primary aspects of a complex software system are the components, which would be the basic building blocks of the system, and the architecture, which describes how the individual components interact so that the overall system possesses the desired behavior. There is a close relationship between Component-Based Software Engineering (CBSE) [2] and Modular programming [3] that emphasizes the importance of dividing the overall functionality of a complex software system into individual functional components that can be developed separately such that each module contains all that is needed to execute a particular aspect of the desired overall functionality. CheckSoft is comprised of different modules/components, each responsible for a distinct functionality as explained in Section 4.2.

CheckSoft components can produce or consume events and, through the events, work collaboratively to achieve the desired overall behavior, as we explain in Section 3. The resulting architecture is what may be referred to as an event-driven architecture (EDA). In a wide ranging survey of event based systems by Hinze et al [4], the authors discuss the role and the modalities for event processing in reactive applications. Etzion et al. [5] discuss the necessity of incorporating event-driven functionality in software systems that must exhibit on-demand and just-in-time behavior. Since in EDA, the event producers are unaware of the nature and the number of event consumers, there is a low coupling between them which contributes to extensibility as new consumers can be added as and when required as well as the scalability of such systems [6].

In such systems, an event is defined as a significant change in state [7] that, in general, must result in the execution of a certain functionality by what is commonly referred to as an event handler. Anvar et al. [8] and Wagner et al. [9] discuss various finite-state-machine (FSM) based approaches for designing event handlers for real-time software systems. The event handler modules in CheckSoft are also based on FSM based logic that is capable of fast rejection of “illegal” state changes reported by the video monitoring system.

Of the various applications where the EDA approach to software architecture design has been found to be effective, the two that are closest to CheckSoft are IoT and smart environments [10]. The networks used in IoT generally involve heterogeneous devices capable of generating a large number of events and it is necessary to integrate, process, and react to the events on the fly. Almeida et al. [11] have proposed a distributed hierarchical architectural model based on Situational Awareness that can support scalability, flexibility, autonomy and heterogeneity demands in distributed IoT environments. With regard to EDA for smart environments, Roda et al. [6] have proposed an architecture for a scalable and collaborative ambient intelligence environment designed for applications such as smart homes, hospitals, health monitoring and for daily life assistance.

That brings us to the previous work in which researchers have addressed the concurrency issues that arise when there is a need to process in real-time a large number of events simultaneously [12], as is the case with CheckSoft. There are generally two important aspects to such software systems: the ability to detect and respond to events occurring in any random order, and ensuring that the software responds to these events within some required time interval. One of the most notable features of CheckSoft is its ability to process concurrent events in a scalable fashion by using multiprocessing with a distributed memory model as discussed in Section 4.1.

2.2 Survey of the Literature in Related Areas

In this subsection, we briefly review other software systems that are related to our work in the sense that these systems involve software architectures for making real-time inferences from video streams of surveillance data. As an illustration, Vezzani et al. [13] have proposed a Service Oriented Architecture (SOA) that uses event-driven communications to
analyze video feeds from multiple cameras for detecting and classifying faces, postures, behaviors, etc. In that sense, this system is mostly for monitoring people, as opposed to monitoring people-object interactions as we do in CheckSoft. There also exists a commercial framework for video surveillance, the IBM Smart Surveillance Engine [14] that is capable of generating real-time alerts for events triggered by changes in the locations of objects. This system again is not about tracking human-object interactions as we do in CheckSoft.

More closely related to CheckSoft — more closely from the standpoint of the end purpose of the software architectures — are the works described in [15] and [16] for video surveillance meant for airport checkpoint security, and in [17], [18], and [19] for retail store automation. The architecture for airport checkpoint security reported in [15] attempts to detect the associations between the bags and the passengers using a rudimentary FSM that is specific to passengers divesting objects and reclaiming them at airport checkpoint security. The manner in which this logic is implemented and, also, lack of multi-processing significantly impacts the scalability of that work. The goal of the work reported in [16] is even more limited — it only seeks to detect abandoned bags. To compare, CheckSoft addresses system scalability with regard to both the number of people and the number of objects with multi-processing and message passing — this was one of the most important considerations in the design of the CheckSoft architecture. Equally important in CheckSoft is the extendibility of the system with regard to the types of interactions between people and objects.

With regard to the previous work on retail store automation, the work reported in [17] and [18] is about just categorizing actions, as opposed to tracking human-object interactions in a fault-tolerant and scalable framework as accomplished by CheckSoft. Another contribution worth mentioning in the context of retail store automation is the work reported in [19] that deals with using cameras and weight sensors for cashierless grocery shopping. The main focus of such a system is to identify object transfers from the shelves to the customer baskets and vice versa. On the other hand, the design we have used for CheckSoft allows the same architecture to be used for different applications (to name just two for highlighting the variety: automatic libraries and airport checkpoint security) with just a tweak of the FSM states and state transitions.

Another area of research that is tangentially related to CheckSoft is video-based security monitoring of what are known as cyber-physical spaces. By cyber-physical space is meant a monitored space with access control. In addition to physical assets, such spaces also may contain cyber assets that need to be protected from unauthorized intrusions by people. Greaves et al. [20] have shown how a virtual perimeter based on different types of sensors, including video cameras, can be used for access control. Another relevant publication in this area is by Tsigkanos et al. [21] where the authors have shown how the physical layout and the topology of the space involved can be analyzed for the level of protection offered by the sensors used against potential threats. Their proposed analysis techniques also includes the dynamics of people movement in the spaces. The approaches used in such systems for detecting unauthorized behaviors by people are generally based on violations of access control and on spatial modeling of people movement. These concepts are not applicable to the goals for which CheckSoft is designed.

3 The Principal Data Structures

CheckSoft is about keeping track of the different entities that are present in a space that is being monitored, and, even more importantly, about keeping track of the interactions between those entities. We refer to the interactions — such as when a human picks up an object — as events. Therefore, we need data structures for the entities and for the events. In keeping with the best practices in modern programming, we represent these data structures by class hierarchies. This organization of the classes as shown in Figs. 1 and 3 allows the functionality that is common to all the classes to be placed in the root class, which makes it more efficient to maintain and extend the code for different applications.

In the two subsections that follows, Subsection 3.1 presents the Entity class hierarchy and Subsection 3.2 the Event class hierarchy.

3.1 The Entity Class Hierarchy

As shown by the inheritance hierarchy in Fig. 1 we use the Java class Entity as the root class for all the entities that CheckSoft is required to keep track of, these being the individuals, the objects, the storage units, etc.

Here is a brief description of the contract of each class shown in Fig. 1.

Entity (Entity): As mentioned previously, this is the parent class of all the entity related classes in CheckSoft.

Human Entity (HumEnt): The subclass HumEnt serves as a base class for different types of human entities that may be present in the space being monitored with the video cameras. As to what these different types of human entities would be depends on the application. In a retail application, the different subclasses of HumEnt would represent the customers and the different categories of employees in the store. For an automated library, the same would be the users and the
librarians, and so on. For airport checkpoint security, the different subclasses of HumEnt would be the passengers and the TSA agents.

**Storage Entity** (StoEnt): The subclass StoEnt can be used as the parent class of other storage related subclasses that tell us how the objects in the space being monitored present themselves to the humans. The objects could be on shelves, in bins, on the floor, etc. An instance of StoEnt may be real or virtual. An example of a virtual instance of StoEnt would a heap of objects created by a passenger dumping his/her belongings directly on a conveyor belt.

**Object Blobs** (OBlob): This subclass in the Entity hierarchy can be used as the parent class for representing different types of objects in the space being monitored. Ordinarily, one would expect an OBlob instance to represent a single object in the space being monitored. However, it is not always possible to discern objects individually. For example, for the airport checkpoint security case, when a passenger divests all his or her belongings on, say, the conveyor belt, all that the cameras would be able to see would be a blob of pixels occupied by the heap. So an instance of OBlob represents what the system “thinks” is an object. It is possible for such an instance to implicitly represent a collection of objects that are not visible separately.

The reader will notice the attribute ID of the Entity root class in Fig. 1. This attribute, inherited by all the subclasses, is a unique integer that is assigned to each instance of type Entity. Our explanation of CheckSoft in this paper uses the notation Hi to refer to that HumEnt whose ID attribute has value i. Along the same lines, the notation Oj will stand for an OBlob instance that was assigned the ID value j. And the kth instance of StoEnt in an explanation will be referred to as Sk. In our diagrams, we will use the iconic representations of the different entities as shown in Fig. 2.

Figure 2: Iconic representation of the different entities in CheckSoft.

Table 2 in the Appendix elaborates on the attributes for the classes in the inheritance hierarchy. Obviously, for each child class, what is shown for it specifically in the table is in addition to what it inherits from the base class Entity.

### 3.2 The Class Hierarchy for the Events

As mentioned at the beginning of Section 3, CheckSoft is about keeping track of the entities and the events that are generated when there is any object related interaction between the entities. This subsection will describe the class hierarchy for the events.

However, before presenting the hierarchy of classes for the events, it is important to mention that we assume that a video-camera client of CheckSoft can track the individuals and identify the object blobs that the individuals are
interacting with and do so on a continuous basis. We assume that the events pertaining to humans interacting with the objects are all hand-based. We also assume that an interaction between a human entity and an object entity that is in a storage entity starts with a HandIn event and ends with a HandOut event as explained below.

More specifically, we assume that the video-camera clients that are used to monitor the space have continuously running processes that can detect the following events:

1. A human entering the monitored area triggers the HumanEnter event and the human exiting the area triggers the HumanExit event.
2. When a human instantiates a new storage entity (such as a cart) or “returns” a storage entity, either the StorageInstantiate or the StorageReturn event is triggered as the case may be. A storage entity is considered returned when it is empty and its user has exited the monitored area.
3. When an object is placed in a storage entity or taken out of it, that triggers a StorageUpdate event which updates the content list of the storage entity. If the space being monitored involves shelves for storing the objects, each shelf would require its own camera for detecting such events.
4. A human hand reaching inside a storage entity triggers a HandIn event and the hand being pulled back triggers a HandOut event. In Fig. 4, the direction of the arrow on the hand extension of the HumEnt icon indicates the direction of the hand movement with respect to the storage container. The direction of the arrow should help the reader figure out whether the corresponding event is HandIn or HandOut.

The Event class hierarchy is shown in Fig. 3. As shown there, we use the Java Class Event as the root class for all events in CheckSoft that are detected by video-camera clients. Different applications of CheckSoft will differ with regard to the types of events and the entities involved in the events. Table 3 in the Appendix elaborates on the different classes in the inheritance hierarchy shown in Fig. 3.

3.3 An Illustration of How the State of the Entities is Stored

Fig. 4 illustrates an example of the different entities involved and the events detected in a people-centric space. The space being monitored can be divided into three main regions: the entry area, the exit area, and the interaction area where people interact with objects. The three different types of entities – HumEnt, StoEnt and OBlobs — are shown, each with its own unique integer. The icons used for the entities are as indicated in Fig. 2.

The example shown in Fig. 4 will generate several different events simultaneously. In the entry and exit areas, the entry of HumEnt H8 and the exit of HumEnt H5 will generate the HumanEnter and HumanExit events, respectively. Similarly, HumEnt H7 instantiating StoEnt S1, and HumEnt H3 returning StoEnt S0 will result in the StorageInstantiate and StorageReturn events being detected. In the interaction area of Fig. 4 many individuals could be interacting at the same time and hence several HandIn, HandOut and StorageUpdate events would be generated simultaneously. It could be that HumEnt H3 has previously placed the object represented by OBlob O8 in the StoEnt S3 and is now retrieving his/her hand, which would trigger the HandOut event. Along the same lines, HumEnt H4 appears in the process of placing an object in StoEnt S7, which would trigger the HandIn event; and so on. The StorageUpdate event is generated whenever the content information of any StoEnt needs to be updated.
Focusing on a specific subset of the interactions in Fig. 4, Fig. 5 illustrates how the state information for the entities is stored in the different data structures. We will consider the interactions involved in HumEnt H1 transferring OBlob O6 from StoEnt S2 to StoEnt S3 in Fig. 4.

There are two interactions relevant here: HumEnt H1 removing OBlob O6 from StoEnt S2 between time t_p to t_q, followed by another interaction in which the same HumEnt places the same OBlob in StoEnt S3 between time t_r to t_s. Each interaction starts with a HandIn event and ends with a HandOut event as shown in Fig. 5(a). Fig. 5(b) shows all the entity instances relevant to the two interactions.

As shown in Fig. 5(b), the StoEnt instances maintain the timestamped information related to the OBlobs instances they contain in the Content data attribute. In Fig. 5(b), before the interaction starts with StoEnt S2 at t_p, S_2.Content = {4, 5, 6} as StoEnt S2, contains the OBlobs O4, O5 and O6 and similarly after the interaction ends at t_q, we have S_2.Content = {4, 5}. On a similar note, before the interaction starts with StoEnt S3 at t_r, we have S_3.Content = {7, 8} as can be seen in Fig. 5(b). Similarly, after the interaction ends at t_s, we have S_3.Content = {7, 8, 6}.

One important point to note here is that during the time of the interaction, when the hands are inside the storage area, the hands may occlude the objects from the camera. Therefore, if the video-trackers generate a StorageUpdate event during the interaction, the content information reported would be inaccurate. It must be ensured that the state of StoEnt S_k is not corrupted when the data reported by the video-trackers is unreliable. The S_k.Update attribute shown in Fig. 5(b) allows updates to the S_k.Content attribute only when it is set to True. To prevent the state of S_k from being inaccurate.

Figure 5: A pictorial description of HumEnt H1 transferring OBlob O6 from StoEnt S2 to StoEnt S3 is shown in (a). An illustration of how the state information of the different entities due to the interactions is stored is shown in (b)
updated during the interaction when a HandIn event involving $S_k$ occurs, $S_k$.Update transitions from True to False and, subsequently, when a HandOut event occurs, $S_k$.Update transitions back to True.

Each HumEnt instance stores locally the ‘before’ and ‘after’ state of the storage containers that it is interacting with. These are stored in the data attributes BufferBefore and BufferAfter of the HumEnt instance. In our example, the HumEnt instance $H_1$ will store the ‘before’ and ‘after’ contents of the StoEnts $S_2$ and $S_3$ in the variables $H_1$.BufferBefore and $H_1$.BufferAfter. A unique key is associated with each such stored state that depends on the IDs of both the HumEnt and the StoEnt. In our example, the key associated with what is stored in $H_1$.BufferBefore and $H_1$.BufferAfter would be $<1,2>$ for the first interaction and $<1,3>$ for the second interaction. In these two keys, 1 is the HumEnt ID and 2 and 3 are the StoEnt IDs involved in the interactions.

An attribute common to all the entities is Ownership that consists of two lists: the OwnedBy list in which the information regarding who owns the corresponding entity is stored, and Owns in which the information regarding what entities the corresponding entity owns is stored. For example, as shown in Fig. 5(b), HumEnt $H_1$ owns StoEnt $S_2$ and hence HumEnt $H_1$ appears in the OwnedBy list of $S_2$.Ownership and StoEnt $S_2$ appears in the Owns list of $H_1$.Ownership. Similarly, the reader can see that the StoEnt $S_3$ is owned by some other HumEnt $H_3$. HumEnt $H_1$ owns Oblobs $O_4$, $O_5$ and $O_6$ and therefore this appears in the Owns list of $H_1$.Ownership.

The data attributes $H_1$.ActionQ and $H_1$.InferenceQ shown in the left panel in Fig. 5(b) are hash tables of queues storing the interaction history for each OBlob that HumEnt $H_1$ interacted with. The interaction history, in the exact temporal sequence of occurrence, is stored for each OBlob in a separate queue. Each interaction is recorded in the following form:

$$ [t - \text{action/inference} - k] $$

where $t$ is the time of the interaction and $S_k$ the StoEnt involved in the interaction.

Regarding the two queues mentioned above, in $H_1$.ActionQ, we store the elementary actions such as adding or removing OBlobs. On the other hand, in $H_1$.InferenceQ, we store the inferences and anomalies detected by the logic of CheckSoft. To illustrate this, for both $H_1$.ActionQ and $H_1$.InferenceQ, we will consider the entries for key 6 in Fig. 5(b), which is the OBlob involved in the interaction. Since OBlob $O_6$ was transferred from StoEnt $S_2$ to $S_3$, the elementary actions in this case are Remove and Add and these are stored in $H_1$.ActionQ as the following string:

$$ [t_q - \text{Remove} - 2], [t_s - \text{Add} - 3] $$

The inferences are stored in $H_1$.InferenceQ as:

$$ [t_q - \text{MoveFrom: Own Bin} - 2], [t_s - \text{MoveTo: Other Bin} - 3] $$

The ownership relationships Own Bin and Other Bin are derived from the fact that StoEnt $S_2$ is owned by HumEnt $H_1$ but StoEnt $S_3$ is not, as shown in $H_1$.Ownership. This interaction in which the OBlob $O_6$ was transferred to StoEnt $S_3$ which belongs to some other HumEnt is an example of what will be detected as an anomalous interaction by CheckSoft.

### 4 Overall System Architecture

The goal of this section is to give the reader a top-level view of the architecture of CheckSoft and the rationale underlying the architectural design. Subsequently, a more detailed presentation of the architecture that describes the roles of the different components will be presented in Section 5.

With regard to the top-level view presented in the next three subsections, we first describe in Section 4.1 how concurrency is exploited for handling the interactions that may occur simultaneously, and, subsequently, in Section 4.2 we present the major modules of the event-driven software architecture. Finally, we provide a high-level overview of how Checksoft’s finite state machine based logic provides significant immunity against noisy data reported by video-trackers in Section 4.3.

#### 4.1 Exploiting Data Parallelism with Concurrency and Communications

As illustrated in Fig. 6(a), the data produced by the video camera clients (displayed by the 6 icons in the top row in the figure) is inherently parallel. Most applications of CheckSoft will involve several video cameras monitoring different sections of the space as shown in Fig. 4. Additionally, any number of individuals may be interacting with an arbitrary number of objects at any given time. Therefore, one can expect an arbitrary number of events to be generated concurrently. In order to not introduce undesirable latencies in reacting to these events, they would need to be processed
Each HumEnt and StoEnt entity is allocated a separate worker process. The master process dispatches events detected by the video-trackers to the different worker processes. The worker processes then run the event handling modules shown below and communicate using MPI as and when required.

The different CheckSoft modules that handle concurrent events are shown in grey boxes. (The subscripted notation $H_i$ refers to the $i^{th}$ HumEnt instance, $O_j$ refers to the $j^{th}$ OBlob instance and $S_k$ refers to the $k^{th}$ StoEnt instance involved in the corresponding events.)

Figure 6: The Overall Architectural Diagram.

in parallel. Obviously, any attempt at exploiting this parallelism must not result in memory corruption and deadlock conditions should the computations being carried out in parallel access the same portions of the memory.

The two basic approaches to achieving concurrency in software are multi-threading and multi-processing. Since threads can be thought of as lightweight processes, one main advantage of multithreading is that it is faster to create and destroy the threads and faster to access the objects in the memory that are meant to be shared by the threads. However, through synchronization and semaphores, multithreading requires greater care in ensuring that the memory meant to be shared by the different objects is not corrupted by the threads accessing the same object simultaneously.

In CheckSoft, we have chosen to use multiprocessing instead. As each HumEnt or StoEnt instance is created, it is handed over to a separate process by the master process that runs CheckSoft. This decentralizes the bookkeeping for keeping track of the different states of each individual and each storage container, as the process assigned to each entity takes care of all such details. This is one of the important reasons for why our software can easily be scaled up. As is to be expected, a collection of processes for similar entities, such as all the HumEnt entities, are clones of the same basic process. We refer to such a collection as a process group. For the purpose of explanation, and as shown in Fig. 6(a),...
CheckSoft is comprised of different modules, each responsible for a distinct functionality. As mentioned in Section 2.1, we use the notation HumEnt\_Group to refer to the HumEnt processes and the notation StoEnt\_Group to refer to the StoEnt processes.

CheckSoft uses multiprocessing with a distributed memory model in which every process in the system has its own private memory. If an event involves any of the HumEnt and/or StoEnt instances, the corresponding worker process executes the appropriate event handling module described in Section 4.2 and updates the corresponding entity state information in its own private memory as shown in Fig. 6(a). Since all of the computations carried out by a process only involve the private memory of the process, it follows that the processes that are in charge of analyzing the human-object interactions must somehow become aware of both the humans and the objects involved. As opposed to using a shared-memory model, we take care of such inter-process interactions through the communication facilities provided by MPI (Message Passing Interface).

CheckSoft uses the standard MPI for intra-communication within each process group and for inter-communication between different process groups. MPI provides us with what are known as communicators for those purposes. The messaging achieved with intra-communicators within each process group can work in both point-to-point mode, in which each process sends a message to one other specific process, and in broadcast mode, in which a process sends a message to all other sibling processes. The messaging achieved with inter-communicators can work only in point-to-point mode in which a process of a particular group sends a message to a chosen process in another process group.

For an example of within-group communications with intra-communicators, let’s say that some aspect of the state of all StoEnt instances needs to be updated at the same time, this would require using an intra-communicator in the broadcast mode. And for an example that requires an intra-communicator in a point-to-point mode, consider an object that has been transferred from one StoEnt instance to another StoEnt instance. In this case, while the receiving StoEnt would know directly from the video cameras that it was in possession of a new object, it would nonetheless need to hear directly from the sending StoEnt instance for confirmation.

The master CheckSoft process uses the MPI’s default communicator, Default\_comm, to dispatch events to all worker process groups, meaning the processes in HumEnt\_Group and in StoEnt\_Group as shown in Fig. 6(a). We denote the intra-communicators within the process groups HumEnt\_Group and StoEnt\_Group by HumEnt\_comm and StoEnt\_comm, respectively. As mentioned earlier, in addition to facilitating within-group communications, the intra-communicators are also needed for the functioning of the inter-communicators.

A particularly useful application of the inter-communicator is in fetching content data from a process in the StoEnt\_Group when a HandIn or a HandOut event is recorded (because, say, a human divested an object in a bin). The data and the entities involved can subsequently trigger the downstream finite-state based logic for checking the legality of the event and the legality of the consequences of the event.

As to how the communicators are actually used for passing messages between the processes and fetching data and results from the processes, that is accomplished with an MPI based function gptwc( ), whose name stands for: “General Purpose Two-way Communication”. This function is general purpose in the sense that it can be used to establish a two-way communication link between any two processes. The process that wants to establish a communication link is called the initiator process and the other endpoint of the communication link the target process. An initiator process sends data to a target process and indicates what operation needs to carried out on the sent data vis-a-vis the data that resides in the private memory of the target process. The target process acts accordingly and sends the result back to the initiator process. The implementational details and how this function is invoked is presented in Appendix B.

4.2 Components of the Event Driven Architecture

As mentioned in Section 2.1 CheckSoft is comprised of different modules, each responsible for a distinct functionality, such as extracting person-object ownership information from the data; establishing and updating associational information related to the possibly changing relationships between the objects and the storage units; monitoring various interactions in the environment; detecting anomalies; and so on.

The highly modular architecture is event-driven as shown in Figure 6(b). The events listed on the left side of the figure trigger specific event-handler modules shown on the right side. The most critical components of CheckSoft are the Interaction and Inference modules which are responsible for analyzing the events and drawing inferences regarding the outcome of each person-object interaction. Each submodule within the Interaction and Inference Module is a finite state machine (FSM) that works independently of the FSMs in all other submodules — independently in the sense that the FSM in a submodule cares only about the changes in the state information of the entities involved in the event that triggered the particular FSM.
The use of FSM logic allows us to endow the modules with event-driven behaviors that possess efficient (with polynomial-time guarantees) implementations. As a result of employing an event-driven state machine model, the event handlers remain idle while waiting for an event, and then, when an event occurs, the relevant event handler reacts immediately. This approach can be thought of as a set of computational agents collaborating asynchronously using event-based triggers. Additionally, an FSM based implementation also allows for easy scalability with regard to all the variables that require an arbitrary number of instantiations and additionally provides flexibility to easily extend software functionalities as and when required.

CheckSoft consists of the following four modules:

**Video Tracker Data Recorder (VTDR) Module:** It is this module that the video camera clients talk to directly. As mentioned earlier, CheckSoft is meant to sit on top of a one or more video camera clients installed in the space being monitored. As we will present in Section 5.1 the VTDR module provides a Java RMI (Remote Method Invocation) [22] based E-API (Extension-API) that a video camera client can use for directly sending its event detection results to CheckSoft. VTDR associates a time stamp with every detection reported by a video camera client, and, as the reader will see later, that plays an important role in the temporal sequencing of the events that may be received simultaneously from multiple video cameras. The VTDR module records the event and storage content information from multiple video-trackers in an encoded format into a concurrent unbounded persisted queue named EventSeq with micro-second latencies.

**Event Dispatcher Module:** This module dispatches the encoded event information in the EventSeq queue sequentially in the temporal order of occurrence for further processing. This triggers the different event handlers (and thus the modules shown on the right side of Fig. 6(b)).

**Interaction Module:** This module is triggered by the HandIn and HandOut events involving HumEnt and StoEnt instances and detects the elementary interactions such as the addition and the removal of OBlobs to and from StoEnt instances. This module has two submodules:

1. **Association Submodule:** This module processes the HandIn and HandOut events and, by monitoring changes in the StoEnt content due to an interaction, establishes associations between the OBlob, StoEnt and the HumEnt instances.

2. **Interaction State Machine Submodule:** This module implements the finite-state machine based logic to keep track of the elementary interactions between the HumEnt instances and the OBlob instances that are present in the different StoEnt instances. The finite-state machine logic associates different states with the entities and checks on the legality of the state transitions — and, thus, adds robustness to the operation of CheckSoft.

**Inference Module:** This module specializes in making inferences from the elementary interactions of the HumEnt instances with each of the OBlob instances that the HumEnt interacted with. After each interaction, this module is triggered by a HandOut event (after the elementary action involving the HandOut event is recorded by the Interaction Module). This module is also triggered by the HumanExit events. When the inference module is triggered, that causes the Data Extractor submodule to extract the interaction history recorded by the Interaction module in a time-sequential manner for each OBlob instance the HumEnt interacted with and sends this data to two concurrently running submodules:

1. **Inference State Machine Submodule:** This submodule implements the finite-state machine based logic to infer higher level interactions from the elementary interactions involving the HumEnt, OBlob and the StoEnt instances.

2. **Anomaly Detector:** This submodule detects anomalous interactions (such as when a non-owner HumEnt interacts with an OBlob and/or StoEnt instance) and raises appropriate alarms and warnings.

Since the higher level interactions as well as the type of anomalies vary with the specific application that our architecture is applied to, we may need to tweak the finite-state machine logic in this module. However, it is important to note that these changes in the logic are expected to be minor and should not require any changes in the overall architectural framework of CheckSoft.

### 4.3 Tolerance to noisy data from video-trackers

The events listed on the left side of Fig. 6(b) are generated by the video-trackers. Such events generally are noisy due to occlusion, missed and false detections, inaccurate localization of objects [20], and ineffective tracking under noisy conditions. It is implicitly assumed that the video camera clients are running the NTP protocol as a background process for staying globally synchronized.
CheckSoft is designed to be robust with respect to missed detections by the video cameras and also with respect to any false detections. To give the reader a sense of what we mean by missed and false detections, note that all the objects in a StoEnt instance may not be detected accurately in every image frame, as can be seen in Figure 7(a). These variations in the detected objects might lead to inconsistencies. An additional source of difficulty arises from the fact that when a hand that is trying to reach an object in a StoEnt moves too suddenly, it may not be detected in one or more frames until the image of the hand stabilizes. CheckSoft provides some protection against such effects by filtering out momentary fluctuations in the detections reported by the video trackers.

Yet another source of difficulty is that when a human hand reaches into a StoEnt instance it will block the objects in the container from the camera. This is illustrated in Figure 7(b). Therefore, to eliminate the inconsistencies introduced due to occlusion, the Interaction Module in Section 5.3 only considers the object content before a hand has entered the storage area and after the hand has left.

The state of the entities are updated by the frequently occurring HandIn, HandOut and StorageUpdate events. It is critical to ensure that the state of the entities don’t get changed by erroneous events reported by the video trackers so that the higher-level reasoning logic of CheckSoft functions as desired. This is done by enforcing consistency in the finite-state logic between the different events related to the same overall person-object interaction as shown by the state diagrams in Fig. 8. In Fig. 8 a state is represented by the grey boxes, the event or condition that needs to be satisfied for a state transition is shown in red and the corresponding output as a result of the transition is shown in blue alongside the arrows.

The state diagram in Fig. 8(a) illustrates how CheckSoft rejects noisy content information reported by video-trackers. The HandleUpdate module in Fig. 6(b), appends the Content data attribute with the latest content of the StoEnt Sk with the corresponding time-stamp t when a StorageUpdate(Sk, t) event occurs only if the data attribute Sk.Update is set to True. This ensures that the content information for any StoEnt is updated only when reliable data is reported by video-trackers. As a case in point, the video-trackers might report erroneous content information during the time of an interaction when objects inside the storage area are occluded by hands. To provide protection against this, when any HandIn event involving StoEnt Sk occurs, Sk.Update is set to False thereby blocking any updates to state of Sk during the interaction. When a HandOut event occurs involving the same StoEnt, Sk.Update is set to True thereby allowing updates to the state of Sk after the interaction is over.

The state diagram in Fig. 8(b) illustrates how noisy HandIn, HandOut events as well as false interactions reported by video-trackers are filtered by the Interaction Module. As mentioned before, every interaction starts with a HandIn event and ends with a HandOut event. Typically a video-tracker monitoring any storage area should report a HandIn event when motion is detected and subsequently report a HandOut event when the motion has completely subdued in storage area. CheckSoft considers an interaction to be valid only if both of these events involving the same HumEnt and StoEnt have been reported in the correct temporal sequence by the video trackers. The Association Submodule
is designed to filter out the noisy hand-based events as shown by the black arrows in Fig. 8(b). The Association Module thereby only processes the hand-based events for a valid interaction and consequently fetches the content before and after the interaction from StoEnt $S_k$ and finally stores it in $H_i$.ContentBefore and $H_i$.ContentAfter respectively.

Also, it is very common for the video-trackers to report false interactions, where an interaction didn’t actually happen but the video trackers report false HandIn and HandOut events indicating an interaction has happened. For such cases, there is no change in the content since an actual interaction has not happened. The Interaction State Machine (shown by the magenta arrows in 8(b)) analyses the content before and after the interaction and records the interaction in $H_i$.ActionQ for further analysis only if there is some change in the content. Otherwise, the interaction is not recorded and thereby false interactions are filtered out. Only the interactions recorded are further considered for analyzing inferences and detecting anomalies by the Inference Module and recorded in $H_i$.InferenceQ (shown by the green arrow).

5 The CheckSoft Modules

The previous section, Section 4, provided a high-level summary of the modular architecture of CheckSoft and also talked about how data parallelism is exploited through concurrent processing as made possible by the MPI standard. The goal of this section is to present a more detailed look at each of the CheckSoft modules.

5.1 Video Tracker Data Recorder Module

We start by reminding the reader that video tracking per se is outside the scope of the system architecture we present in this paper. That is, we assume that a video tracker unit is implemented externally and provides our system with the information related to the occurrence of various kinds of events mentioned in Section 3.2. As mentioned before, any arbitrary number of such video-trackers might be employed to monitor a space and thereby it is critical to design an interface that would allow CheckSoft to operate vis-a-vis any arbitrary number of video cameras.

The main purpose of the VTDR module shown in Figure 9(a) is to provide a Java’s RMI (Remote Method Invocation) [22] based plug-n-play interface for the software clients running video cameras. In the language of RMI, a client refers to the machine that wants to invoke a certain functionality in the namespace of another machine, which is referred to as the server. The distributed object programming made possible by RMI is founded on the tenet that to a client a remote object should appear as if it were available locally.
In other words, after a client has located the remote object on the server, the client’s invocation of the methods of the server object should have the same syntax as the methods of an object local to the client. That is, as long as the client implements the functions declared in the E-API (Extension Application Programming Interface) of the VTDR module, the VTDR module and the client would be able to exchange information seamlessly. By calling on its RMI stub classes, the client would be able to write information to VTDR server’s memory.

The E-API made available by the VTDR Server is shown in Figure 9(a). The Blackboard interface is a pure interface with the function declaration of the function that is implemented in the Java class VTDRServer. The function signature is as follows:

```java
void recordEventSequence(Event E)
```

where Event is a superclass of all events that are detected by the video tracker client. Therefore, at runtime, an argument of type Event will actually be a derived instance of the specific event depending on the application.

As each event of the type listed in Section 3.2 occurs, the video tracker client software invokes the `recordEventSequence()` function on the stub of the VTDRServer class. VTDR’s E-API sits on top of Java RMI, which allows for asynchronous interactions between the VTDR module and multiple video tracker clients. This design allows CheckSoft to operate vis-à-vis any arbitrary number of video cameras monitoring the space.

The information provided by multiple video-tracker clients through the E-API is encoded and appended concurrently to a queue named EventSeq. This provides a buffer between the video-tracker clients (producers) and the downstream CheckSoft event handler modules (consumers) which facilitates CheckSoft to process events independent of the incidence rate of events.

In our implementation, we use the Chronicle-Queue (CQ) which is a distributed unbounded persisted queue used for high performance and latency-critical applications. It uses ‘appenders’ that write data to the end of the queue and ‘tailers’ that read the next available data in the queue without deleting any data. In our design shown in Fig. 9(b), each video-tracker client records the event information to the EventSeq queue concurrently using an appender. Then the master process of CheckSoft reads the event data using a tailer and dispatches the information to different worker processes.

The use of CQ in the design of the VTDR module offers the following main advantages:

1. It allows fast communication between the process that runs VTDRServer (writes event data) and the master process of CheckSoft (reads and dispatches event data to other worker processes).

---

4When a software system defines an E-API, that makes it much easier to write code for plug-n-play modules for that system. Technically speaking, an E-API for a software system is just like a regular API, except that the E-API’s functions are meant to be implemented by an external entity.

5https://github.com/OpenHFT/Chronicle-Queue
2. It provides data persistence through memory-mapped files with no data loss and additionally storing the data
to disk periodically for post-facto analysis.
3. It is highly suitable for real-time applications that demand high throughput involving a large number of events
with low latency because it uses off-heap memory which is not affected by garbage collection overheads.
4. It supports concurrent read and write operations and guarantees total ordering of messages. For us this ensures
that each video-tracker client appends the event data to the queue in the exact temporal sequence of occurrence.

It is important to note that a client downloads only a stub version of the VTDRServer class and the client only knows
about the signature of the function of this class that is declared in the Blackboard interface. The client only has to
program to the interfaces of the root classes in our software system and has no access to any of the implementation
code in the server class and that creates maximum separation between our software architecture and the code in the
video-tracker module. Additionally, the VTDR server and the video tracker clients could be running on different
machines in a computer network.

5.2 Event Dispatcher Module

The concurrent event information from the video trackers is recorded in the following encoded format:

[Event type, Event time, Entity Information]

The master process for CheckSoft reads the encoded event information from the EventSeq queue sequentially in the
temporal order of occurrence and broadcasts it to the HumEnt and StoEnt worker processes using the Default_comm
communicator as shown in Figure 6(a).

The worker processes decode the event data received from the master process. From the Entity Information, the entities
involved in each event are determined and the worker processes assigned to the corresponding entities involved then
call the appropriate event handlers to perform a variety of functions/computations based on the Event Type, as shown in
the Table 4 in the Appendix.

5.3 Interaction Module

This module is responsible for detecting the elementary interactions such as the addition and the removal of OBlob
instances to/from the StoEnt instances and associating these entities with the HumEnt entity involved in the interaction.
This module is triggered for every interaction between HumEnt and OBlob instances contained within StoEnt instances.
Since these interactions can happen simultaneously in the real-world, this module is implemented such that it can handle
concurrent events.

Additionally, the Interaction Module is designed to be robust to various sources of noisy event data reported by the
video trackers such that the higher-level inferences made by the modules downstream are less prone to errors. We had
provided a brief overview of the approach in Section 4.3. In this section we provide a detailed discussion of the same.

More specifically, the Interaction Module provides immunity against the following:

1. noisy hand-based events and false interactions by enforcing consistency in the finite-state logic between the
different events related to the same overall person-object interaction.
2. inconsistent storage content information as shown in Fig. 7 due to the following:
   (a) false and missed object detections in the storage area by filtering out momentary fluctuations in the
detections reported by the video trackers.
   (b) occlusion of objects by hands during an interaction by determining the object content before a hand has
       entered the StoEnt area and after the hand has left.

The Interaction module has two submodules:

5.3.1 Association Submodule

This submodule processes the HandIn and HandOut events and by monitoring changes in the StoEnt content due to
an interaction, establishes associations between the OBlob, StoEnt and the HumEnt instances. To elaborate further on
this, let us refer to Fig. 10. There is a continuous association between OBlob and StoEnt instances since we know the
content information at any given timestamp reported by the video-trackers. An association between a HumEnt instance
and a StoEnt instance is formed at the time of interaction. However, there is no direct association between HumEnt and
OBlob instances. This submodule monitors the change in the content of the StoEnt before and after an interaction and
figures out the change in the OBJob instances as a result of the interaction and passes this information of the OBJob, StoEnt and the HumEnt instances involved in any interaction to the Interaction State Machine Submodule.

Let us now refer to the Figure 11 to understand how the Association Submodule is designed to handle concurrent events. Let us consider an interaction between HumEnt $H_i$ and StoEnt $S_k$, that in general starts with a HandIn event at time $t_{in}$ and ends with a HandOut event at time $t_{out}$. Let us denote the process assigned for the $H_i$ instance as $PH_i$ and the process assigned for the $S_k$ instance as $PS_k$.

When a HandIn event occurs, $PS_k$ sets $S_k$.Update to False which prevents any erroneous updates to $S_k$.Content during the interaction when objects might be occluded from the camera by hands. The $S_k$.Update value is set to True when the HandOut event involving the same HumEnt $H_i$ and StoEnt $S_k$ occurs. On the other hand, $S_k$.InUse is set to True when the interaction begins and subsequently set to False at the end of the interaction. During both the HandIn and HandOut events, there would be a gptwc() function call using the inter-communicator Inter_comm between $PH_i$ and $PS_k$, where the process $PH_i$ would be the initiator process and the $PS_k$ would be the target process.

The HumEnt instances have a specialized buffer data structure that is designed to store information pertaining to concurrently occurring interactions temporarily as well as filter out noisy invalid events effectively as will be explained later. Each entry in this buffer stores the content information ($S_k$.Content($t_i$)), at interaction time $t$ returned by a gptwc() function call between $PH_i$ and $PS_k$ with an associated unique key pair ($<i,k>$), which denotes the IDs of the interacting HumEnt $H_i$ and StoEnt $S_k$ entities. Each HumEnt instance has two such buffer data attributes BufferBefore and BufferAfter, for storing the results returned by a gptwc() function call for HandIn and HandOut events respectively.

During a HandIn event, $PH_i$ initiates a request to $PS_k$ and $PS_k$ would be responsible for fetching the content before time $t_{in}$ and filtering the noise across multiple time-stamps before that and send the noise-filtered content information ($S_k$.Content($t_{in}$)) back to $PH_i$ and this would be pushed into $H_i$.BufferBefore as:

$$S_k.Content(t_{in}) \xrightarrow{push} H_i.BufferBefore$$

Similarly during a HandOut event calling the gptwc() function would provide the noise-filtered content information ($S_k$.Content($t_{out}$)) after time $t_{out}$. The result would be pushed into $H_i$.BufferAfter as:

$$S_k.Content(t_{out}) \xrightarrow{push} H_i.BufferAfter$$

Now, it will be checked if there is a matching entry with the same key pair ($<i,k>$) in $H_i$.BufferBefore and $H_i$.BufferAfter, which would denote that this corresponds to a valid interaction between the unique pair of HumEnt $H_i$ and StoEnt $S_k$. If a matching entry is found, these entries are popped from $H_i$.BufferBefore and $H_i$.BufferAfter as:

$$H_i.BufferBefore \xrightarrow{pop} H_i.ContentBefore = S_k.Content(t_{in})$$

$$H_i.BufferAfter \xrightarrow{pop} H_i.ContentAfter = S_k.Content(t_{out})$$

The Process $PH_i$ then computes the objects added ($O_{ADD}$) and removed ($O_{REM}$) by computing the set difference as follows:
Figure 11: MPI Communication and computations in the Association Module

\[ O_{ADD} = H_i.\text{ContentAfter} - H_i.\text{ContentBefore} \]
\[ O_{REM} = H_i.\text{ContentBefore} - H_i.\text{ContentAfter} \]

The extracted information is then passed to the Interaction State Machine Submodule.

Now, if there is a HandOut event without a matching HandIn event between HumEnt \( H_i \) and StoEnt \( S_k \), then there would be no entry in \( H_i.\text{BufferBefore} \) with the key pair \(<i, k>\) and the system would detect a Noisy HandOut event and exit with an operation to flush out the erroneous entry in \( H_i.\text{BufferAfter} \). The Interaction State Machine will not be triggered in this case.

Similarly, if there is a previous HandIn event without a matching HandOut event, between HumEnt \( H_i \) and StoEnt \( S_k \), then there would be a previous entry in \( H_i.\text{BufferBefore} \) with the key pair \(<i, k>\) however this error will not be propagated any further because the Interaction State Machine is only triggered if there is a matching HandOut event.

This validates the fact that only a matching HandIn and HandOut event triggers the Interaction State Machine and all other noisy invalid HandIn and HandOut events would be filtered out. This design provides immunity against various types of noisy event data as well as handles concurrent interactions reported by video-trackers.\footnote{In some cases, an end user might want to keep track of these interactions for a group comprising of multiple individuals together. For example, in an airport checkpoint security it would be beneficial to keep track of passengers traveling together as a group so that there are no false alarms when members of the same group divest/collct common items. Another possible scenario is keeping track of families shopping together in a retail store such that they can be billed to a single account. In such cases we can associate all the members of the group to a single HumEnt instance with a single ID. The design of the Association Module can also effectively handle complicated situations where multiple members in a group associated with the same HumEnt instance interacts with multiple StoEnt instances at the same time, without any additional changes. This is because each such interaction will have different key pairs \(<i, k>\), where \( i \) will remain same but \( k \) will be different for different StoEnt instances.}

5.3.2 Interaction State Machine Submodule

This module implements the finite-state machine based logic to keep track of the elementary interactions between the HumEnt instances and the OBlob instances that are present in the different StoEnt instances. By monitoring the changes in the contents in the particular StoEnt instance the Interaction State Machine can determine if any OBlob were added and removed as a result of the interaction.

The states shown in Figure 12(a) represent the elementary interactions between the three instances, HumEnt \( H_i \), StoEnt \( S_k \) and OBlob \( O \), that would typically be involved in any interaction. Let us consider the following three cases:
Figure 12: The Interaction State Machine diagram for each Interaction between HumEnt \(_i\) (\(H_i\)) and StoEnt \(_k\) (\(S_k\)) at time \(t\) is shown in Fig. (a). An example of the elementary action history stored in \(H_i.ActionQ\) for each OBlob (stored in a different row) that the particular HumEnt \(H_i\) interacted with is shown in Fig. (b).

1. If an object \(O_{ADD}\) was added to \(S_k\) (\(O_{ADD} \neq \emptyset\)) at time \(t\), then the string \([t - A - k]\) is appended to the queue corresponding to OBlob \(O_{ADD}\) in the data attribute \(H_i.ActionQ\).

2. Similarly, if an object \(O_{REM}\) was removed (\(O_{REM} \neq \emptyset\)) from \(S_k\) at time \(t\), then the string \([t - R - k]\) is appended to the queue corresponding to OBlob \(O_{REM}\) in the data attribute \(H_i.ActionQ\).

3. However, if no objects were added to/removed from \(S_k\) (\(O_{ADD} = \emptyset\) and \(O_{REM} = \emptyset\)), it could either mean that this is a false interaction reported by the video trackers or the HumEnt \(H_i\) interacted with \(S_k\), but did not displace any objects and thus no changes are made to \(H_i.ActionQ\).

An example of the elementary action history stored in \(H_i.ActionQ\) for each OBlob that the particular HumEnt \(H_i\) interacted with can be seen in Fig. 12(b).

5.4 Inference Module

This module specializes in making inferences from the elementary interactions between the HumEnt instances and the OBlob instances. After each interaction, this module is triggered by a HandOut event (after the elementary action involving the HandOut event is recorded by the Interaction Module). This module is also triggered by the HumanExit event. The input to this module is the data attribute \(H_i.ActionQ\), where \(H_i\) is the HumEnt who is either involved in the interaction or is exiting the monitored area.

Since the higher level interactions as well as the anomalous interactions vary with the specific application that our architecture is used in, the finite-state machine logic in this module needs to be tweaked. Hence, it is particularly important to design this module such that this does not involve any changes in the overall architectural framework and so that these changes in the logic are minor and can be easily updated, specific to the requirements of the application.

5.4.1 Data Extractor

This submodule extracts the interaction history from the ActionQ of the HumEnt for each OBlob that the HumEnt has interacted with. If the Inference Module is triggered after an interaction (by the HandOut event), then only the information for the OBlob that was involved in the interaction is extracted. However, if the Inference Module is triggered by the HumanExit event then the Data Extractor extracts the information for every OBlob that the exiting HumEnt interacted with.

For example according to Figure 12(b), the latest interaction of the HumEnt was at time 136 with OBlob \(O_{11}\). So the HandOut event at this time triggers the Inference module and the Data Extractor would fetch the following string:

\[
[83 - R - 5], [101 - A - 4], [118 - R - 4], [128 - A - 4], [136 - R - 4]
\]

The sequence of elementary actions\(^7\) for the particular OBlob is sent to the Inference State Machine submodule and the information pertaining to the StoEnt and OBlob instances involved in the interactions are sent to the Anomaly Detector, as shown in Fig. 13. For OBlob \(O_{11}\) in Fig 12(b), the sequence of elementary actions ((\(R, A, R, A, R\)) is sent to the Inference State Machine and the information for OBlob \(O_{11}\) and StoEnts \(S_4\) and \(S_5\) is sent to the Anomaly Detector.

---

\(^7\)An elementary action can either be Add or Remove, which is represented as ‘A’ or ‘R’
5.4.2 Inference State Machine Submodule

This submodule implements the finite-state machine based logic to infer the higher level interactions and the ownership relationships between the HumEnt, OBlob, and StoEnt instances. More specifically, this submodule processes the causal relationship between the elementary actions to understand higher level interactions based on the rules of interaction specific to the application. The application-specific inference logic can be customized based on the requirements, as discussed in Appendix C.

If the higher-level interaction inferred alters the ownership relationship then a control signal to Set Ownership is sent to the Anomaly Detector. Otherwise, the control signal to Test Ownership is sent to the Anomaly Detector. Typically for the applications we are considering, the first interaction is what determines the Ownership relationship between HumEnt instances and OBlob instances.

5.4.3 Anomaly Detector

This submodule detects anomalous interactions based on ownership relationships and raises appropriate alarms when anomalies are detected. This submodule runs in parallel vis-a-vis the Inference State Machine, that dictates its mode of operation.

When the Inference State Machine infers any change in ownership relationships, it indicates that the Anomaly Detector should set the ownership information and remember it for detecting anomalies in successive interactions. For example in an airport checkpoint security application, this is done by appending the OBlob Oj and StoEnt Sk information in the Owns list of the data attribute Hi.Ownership.

On the contrary, when any other type of higher-level interaction is inferred that does not change the ownership relationship, the Inference State Machine indicates that the Anomaly Detector should test if the entities involved in the interaction belongs to HumEnt Hi. For testing the ownership of the entities OBlob Oj and StoEnt Sk we would check if it exists in Hi.Ownership. If it does not exist in Hi.Ownership, then Hi is not the owner and then an appropriate alarm or warning message is issued.

Each of the latter two submodules have their own handlers to handle application-specific tasks based on the outcome of the inferences and anomaly detections.

In this section, we are only showing the architectural highlights of the Inference Module to demonstrate that CheckSoft can be used in different applications. Obviously, the rules of person-object interactions are application-specific and hence the FSM based inference logic must be tweaked for each application. The inference logic for the Airport Checkpoint Security and Automated Retail Store applications is described in Tables 5 and 6 respectively in Appendix

---

The actual owner can be determined by a gptwcl() function call using Inter_comm to fetch the ownership information of the corresponding entity.
To show examples of higher-level interactions inferred and anomalies detected by the Inference Module from the elementary action history in these applications, we refer the reader to Fig. [17]

6 Scalability and Deadlock-Free Operation

In this section we present the main features of our software design that guarantee scalability and deadlock-free operation. The supplemental material includes a Petri Net based modeling of the software for verification of deadlock-free operation and liveness properties.

CheckSoft uses multiprocessing with a distributed memory model in which every process in the system has its own private memory and all of the computations carried out by a process only involve the private memory. Obviously, the processes that are in charge of analyzing human-object interactions must somehow become aware of both the humans involved and the objects in the storage containers. As opposed to using a shared-memory model, we take care of such inter-process interactions through the communication facilities provided by MPI, as shown in Fig[14] The isolation between the processes achieved in this manner eliminates any possibility of the processes stepping on one-another for accessing shared resources, which is a major reason for deadlock in shared memory systems.

![Figure 14: CheckSoft architecture using multiprocessing with a distributed memory model.](image)

The master process reads the encoded event information recorded in the EventSeq queue mentioned earlier in Section [5.1] and loads the next available entry into its local memory. This information is then broadcast through MPI communications to the different HumEnt and StoEnt worker processes, as shown in Fig[14] When there is a HumanEnter or a StorageInstantiate event, a previously created worker process is launched and the corresponding entity information is stored in the local versions of the principal data structure derived from the base class Entity. For example, the worker processes in the HumEnt group (PH₁ to PHₙ) each has a HumEnt instance (H₁ to Hₙ respectively) in its own local memory to store the corresponding human entity information. Similarly, the worker processes in the StoEnt group (PS₁ to PSₖₘ) each has a StoEnt instance (S₁ to Sₖₘ respectively) in its own local memory to store the corresponding storage entity information. When there is a HumanExit or StorageReturn event, these worker processes are freed up and made available for new entities.

We will now use an example to illustrate the fact that each worker process only needs to work with its own local memory. Assume that a StorageUpdate event has just been recorded for a StoEnt instance Sₖ. This would cause the attribute Sₖ.Content of the Sₖ instance to be updated by the worker process PSₖ if Sₖ.Update is True. To avoid erroneous updates during an interaction involving Sₖ, the worker process PSₖ sets Sₖ.Update to False at the beginning of the interaction and subsequently sets it back to True at the end of the interaction.

It is important to note that only the process PSₖ has access to this content information of Sₖ. In general, when a process needs some information from another entity, it fetches the information using MPI’s communication primitives. In our example, when there is a HandIn or HandOut event due to an interaction between a HumEnt Hᵢ and a StoEnt Sₖ, the Interaction Module is triggered in order to figure out what object has either been placed in the StoEnt instance or taken out of it. For that, the HumEnt worker process PHᵢ needs the storage content of the StoEnt entity Sₖ before the HandIn or after the HandOut event. Towards that end, the process PHᵢ initiates a gptwc() function call that results in PSₖ fetching the Sₖ.Content before/after the event. Subsequently, PHᵢ stores this information temporarily in the Hᵢ.BufferBefore buffer or the Hᵢ.BufferAfter buffer, depending on whether the primary triggering event was HandIn or HandOut. The difference between the content before and after a particular interaction is then analyzed to
figure out what object was involved in the interaction and the elementary actions associated with the interaction is then recorded by the process $PH_i$ in $H_i, ActionQ$. In this manner, only the worker process $PH_i$ is in charge of recording all the interactions related to the $HumEnt H_i$. All the elementary interactions involving any $HumEnt H_i$ can be found in the data structure $H_i, ActionQ$. As a consequence, at the end of every interaction involving a $HumEnt H_i$ or when a $HumEnt H_i$ exits the area being monitored by CheckSoft, this aspect of our software design allows for all high-level inferences related to the $HumEnt H_i$ to be made immediately and without any resource contention.

This design makes CheckSoft scalable to any number of $HumEnt$, $StoEnt$ and $OBlob$ entities. The level of concurrency, which is the number of active processes or entities at any given point of time, is, of course, limited by the computational resources available on the hardware platform running CheckSoft. The event handlers of CheckSoft are non-preemptive and hence for handling certain events, a task may need to wait if the required process is busy handling a previous task or when communication between processes is required. In general, a task would wait until all the required processes are available and this might incur unwanted latency in handling events, which should be within reasonable limits of tolerance. The scalability related aspects have been analyzed in Section 7.1.2.

7 Performance and Validation

For validation, we have adopted a dual approach in which we use a simulator to study the scalability and robustness of CheckSoft and use actual video trackers to analyze other aspects of the system. This is because it would be highly non-trivial to also analyze the scalability and robustness issues with real video data in a laboratory setting.

In this section, we first report in Section 7.1 on the scalability results that we have obtained with the help of the simulated data involving a large number of $HumEnt$, $StoEnt$ and $OBlob$ entities being monitored by a large number of video trackers. The scalability study involves investigating two performance parameters: level of concurrency and latency with simulated data for two different types of applications of CheckSoft: airport checkpoint security and automated retail store. The simulated data, after noise is added to it, is also used to validate the robustness of CheckSoft with respect to errors made by event detectors.

Subsequently, in Section 7.2, we demonstrate with real-time data from several cameras that CheckSoft can indeed process feeds simultaneously from multiple video trackers.

7.1 A Simulation Based Large-scale Testing of CheckSoft

![Figure 15: Validation Framework for CheckSoft.](image)

We have tested the logic of CheckSoft with a simulation-based validation framework called CheckSoftValidate, whose “architecture” is shown in Fig 15. The validation framework can be used for testing and evaluating the rules used for associating human entities with the objects they interact with and for analyzing the outcomes of these interactions. The front-end to the validation framework is a UI on the client machine that can be used to set the different parameters of a simulated environment as shown in Fig. 16. The UI on the server machine displays the complete state of the monitored area and any detected anomalies, as inferred by the logic of CheckSoft.

As shown in Fig 15, an important component of CheckSoftValidate is a video-tracker simulator module running on the client machine that generates the event and storage content information which is input to CheckSoft. The video-tracker simulator models the monitored area symbolically and emulates application-specific human behavior as closely to the

---

*The verification framework is available at the following url:

https://github.com/sarkar-rohan/CheckSoft

where a user can run the CheckSoft simulator and investigate its performance with respect to all the design parameters.*
real world as possible. The simulator is multi-threaded where each thread symbolically represents a video-tracker detecting concurrent events. The threads upload the event information parallely to the server memory.

The number of video trackers monitoring the simulated area as well as the number of human entities, storage entities used, objects in the simulated environment and the number of human and storage entities that are active at any moment of time are controlled by values for the relevant UI parameters mentioned in Table 1(a). The rate at which the humans enter/exit the simulated environment and storage entities are instantiated/returned as well as the frequency of interactions with objects is controlled by the values for the relevant UI parameters mentioned in Table 1(b). We can also simulate noise in the environment which generates false hand-based events as well as false and missed detections of objects in the storage entities, which are controlled by the values for the relevant UI parameters mentioned in Table 1(c). The values of the parameters set in the UI specifically in Table 1(b) and (c), that control the interactions and events as well as the effect of noise in the simulated data are merely the mean values for what are otherwise random numbers.

CheckSoftValidate uses the data generated by the video tracker simulator for testing the scalability of the system as the number of people, the storage units, and the objects are increased. Besides, the validation framework verifies the operation of the overall decentralized system by testing the E-API that allows CheckSoft and the Video Tracker Simulator to work in two different machines in a network.

As shown in Fig [15] CheckSoftValidate compares the results inferred by the logic of CheckSoft with the ground truth generated by the simulator and computes the accuracy of CheckSoft under different test scenarios, generated by varying the different parameters in Table 1(a), (b) and (c). The results of this comparison are shown in the GUI displayed in Fig. [17] for Airport Checkpoint Security and Automated Retail Store applications respectively.

### 7.1.1 Verification of FSM based Inference Logic for Different Applications

The inference logic presented in Tables 5 and 6 is tested using the CheckSoftValidate framework. In this subsection we are going to briefly discuss the verification results and refer the reader to Appendix C for a more detailed discussion regarding the same.

---

**Table 1: Input parameters for simulator to generate stochastic event sequences.**

| Parameter | Description |
|-----------|-------------|
| (a) nVideoTrackers | Parameters that control the number of entities and video-trackers monitoring the simulated environment |
| nHumans | Number of Humans entities in total. |
| nStorages | Number of StoEnt entities in total. |
| nObjects | Number of O Blob entities in total. |
| maxLevelConcurrency | Maximum number of allowed active HumEnt and StoEnt entities at any given time instant. |
| (b) eventList | List of all possible events [HumanEnter, HumanExit, HandIn, HandOut, StorageInstantiate, StorageReturn, StorageUpdate] |
| eventPDF | Probability of the corresponding event in eventList to be drawn at any time step (basically a PDF). The probabilities determine the frequency of the events and control the rate at which humans enter/exit the simulated environment, instantiate/return storage units and interact with objects etc. |
| actionList | List of all possible higher level interactions depending on the specific type of application. This list includes the anomalous interactions as well. |
| actionPDF | Probability of the corresponding action in actionList to be drawn at any time step (basically a PDF). The probabilities determine the randomized sequence of events for the different interactions that emulate application-specific behavior of any HunEnt entity. |
| maxInteraction | Maximum number of interactions allowed for each HunEnt entity. |
| (c) noisyHandEventPDF | Probability of the hand-based events (HandIn and HandOut) to be corrupted by noise. The probabilities determine the effect of noise in the sequence of hand-based events generated. |
| noisyObjDetectProb | The probability that a particular type of object will be detected wrongly (due to false or missed detections) and the storage content would be corrupted by noise. |
| maxNoisyContentPerc | The maximum extent that the content of any StoEnt will be affected by noise. This determines the maximum percentage of image frames that are corrupted by noise before and after interactions. |

---
Figure 16: The main GUI of CheckSoft.

Figure 17: GUI that shows the interaction history, detected anomalies for an exiting human and verifies the different software modules of CheckSoft for Airport Checkpoint Security and Automated Retail Store applications respectively.

**Airport Checkpoint Security Application**

Fig. [17a] shows how CheckSoft draws inferences about each item that a particular passenger interacted with and raises appropriate warnings or alerts.
It can be easily seen that CheckSoft can correctly verify if passengers collected their own items in which case no anomalies are reported. It can also raise warnings when passengers leave behind their items and raise security alerts when any passenger either moves an item from or to a tray that is not their own or collects an item that does not belong to them.

**Automated Retail Store Application**

Fig. [17](b) shows how CheckSoft draws inferences about each item that the customer interacted with and raises appropriate warnings if some item is misplaced.

It can be easily seen that CheckSoft can accurately draw inferences regarding how many items of each type were purchased, inspected and returned as well as infer which shelves any particular item has been misplaced to.

### 7.1.2 Scalability

Scalability refers to CheckSoft’s ability to track person-object interactions on a continuing basis when it has to deal with a large number of person entities, storage containers, and objects. The number of these entities in the simulated environment is controlled by the $n_{\text{Humans}}$, $n_{\text{Storages}}$ and $n_{\text{Objects}}$ parameters in Table 1(a). We test for scalability through latency at a given concurrency level. The concurrency level is defined as the total number of worker processes that can simultaneously be active. The reader would recall, a worker process is assigned to each new $\text{HumEnt}$ instance and to each new $\text{StoEnt}$ instance. This is controlled by the maxLevelConcurrency parameter in Table 1(a). The maximum level of concurrency depends obviously on the computational resources available to run the CheckSoft software. As a case in point, in our simulations with CheckSoftValidate, we have no problems running CheckSoft at a concurrency level of 200 on a VM with 24 vCPU and 8 GB RAM as shown in Fig. [16]. We are able to do so for both the application domains mentioned in the introduction to Section 7 – the airport checkpoint security domain and the automated retail domain.

The number of video-trackers monitoring the simulated environment is controlled by setting the $n_{\text{VideoTrackers}}$ parameter in Table 1(a). The simulated data in the previous paragraph was generated using 50 threads uploading event information parallely on the server memory. This validates that multiple video-trackers can asynchronously and simultaneously record data using the Blackboard interface of CheckSoft. Therefore, CheckSoft can operate vis-a-vis any number of video-trackers that connect with it on a plug and play basis through the E-API. We have also validated this with actual video-trackers in Section 7.2.

By latency at any given level of concurrency we refer to the time taken by CheckSoft event handlers to process any event from the time it was first detected. This metric helps us understand the responsiveness of CheckSoft to different types of events for a specific level of concurrency. Fig [18] shows the result of an experiment in which the level of concurrency was varied from 50 to 200 and the average latency for each event type was then averaged over 10 experiments.

![Figure 18: Average Latency for the different event types](image)

As can be seen in Fig [18], the average latency of CheckSoft at a concurrency level of 200 is well within the reasonable limits considering the fact that the time constants associated with typical human-object interactions are of the order of a second if not longer. Fig [18] also shows that the average latency increases at a slow rate as the number of active processes increases and therefore CheckSoft would scale well to even higher levels of concurrency.
The HandIn and HandOut events involve MPI communication between one of the HumEnt and one of the StoEnt worker processes and trigger additional FSM based event handling subroutines that filters out noisy events and draws inferences at the end of every interaction and hence has the highest response time. The HumanEnter, HumanExit, StorageInstantiate and StorageReturn events require collective operations within the HumEnt_group or StoEnt_group and have roughly similar response time because of which the curves overlap. The StorageUpdate event involves only one of the StoEnt worker processes and only updates the latest storage content information for the corresponding StoEnt. Since the event handlers for these events do not involve any computation and MPI communication, these events have the lowest response time.

### 7.1.3 Tolerance to Noise

The video-tracker simulator part of CheckSoftValidate was designed specifically to generate randomized data that would correspond to noisy hand-based events as well as erroneous storage content for testing the tolerance of CheckSoft to measurement and event uncertainties.

| Occurrence of actual Hand-based Events | Yes | No |
|----------------------------------------|-----|----|
| Yes                                    | CheckSoft is triggered and the interaction is analyzed | CheckSoft is not triggered and the interaction is missed |
| No                                     | CheckSoft is triggered and the incorrect interaction information can be filtered out by Interaction Module | CheckSoft is not triggered since there is no interaction |

![Figure 19: Tolerance of CheckSoft to different types of missed or false hand-based events](figure)

The probability supplied through the simulation parameter noisyHandEventPDF in Table 4(c) is responsible for generating the noisy hand-based event data. Fig 19 describes the effect of missed or false hand-based events. While CheckSoft can filter out false event detections to some extent, a missed hand-based event would not even trigger CheckSoft and hence it is important that the hand-based event detectors have a low false negative rate as explained in Fig 19.

![Figure 20: Tolerance of CheckSoft to Storage Content Noise due to false and missed object detections.](figure)

The simulation parameter noisyObjDetectProb in Table 4(c) controls the probability of missed and false detections of any OBlob in a StoEnt. At the same time, the parameter maxNoisyContentPerc shown in the same table controls the extent to which the content in any StoEnt is corrupted by noise. CheckSoft uses a polling based noise filtering algorithm to filter out the noise before and after interactions across the content information for multiple time-stamps. Fig 20 shows how the accuracy of CheckSoft decreases as the values supplied for the parameters listed here increase.
because there is greater sensory noise in recognizing the objects that naturally leads to reduced overall accuracy. It gives us a rough estimate of the accuracy needed from the video trackers detecting objects in the storage units. The probability of missed and false detections and the extent to which the content information is corrupted by noise should be such that the accuracy of CheckSoft remains within the region that is marked by dark green color. The red color in Fig [20] indicates low tolerance to noisy content information.

7.2 Validation with video-based data from multiple video-trackers

While we have tested the scalability of CheckSoft and its robustness to noise using simulators, we have used real video trackers to establish that CheckSoft can indeed process feeds simultaneously from multiple video trackers operating in real-time. Our experimental setup is a simple retail-store application with shelves storing different types of objects.

Figure 22: The video-trackers track people and detect human entry and exit events from the video-feed of overhead cameras.

Figure 23: The video-trackers track people and detect interactions with shelf instances from the video-feed of an overhead camera.

It would be highly non-trivial to also analyze the scalability and robustness issues with real video data in a laboratory setting. Hence our dual approach in which we use a simulator to study the scalability and robustness of CheckSoft and actual video trackers to analyze other aspects of the system.
For experiments with real video trackers, we established a zone in our laboratory with an array of open shelves. The zone was monitored with eleven cameras and each shelf has two racks each having its own camera for recording the content of the shelf and any changes in the content. The eleven area based cameras were used to monitor humans as they approached the shelves or retracted away from them.

The video feeds from all the cameras are processed by two PC class client machines. The client machines allot separate processes for the video-trackers hooked to each camera. The VTDR module on the server side, shown in Fig 21 provides a Java RMI (Remote Method Invocation) based plug-n-play interface for the software clients running the video-trackers. The video trackers directly call the E-API using the RMI stub classes for uploading the event information asynchronously and concurrently to the server memory, as mentioned in details in Section 5.1.

Figure 24: The video-trackers track hand movement inside the shelf (detection for four previous time instants are shown in blue and tracking shown by red lines in the images on the left side) and recognize objects in different shelves before and after interactions from the video-feed of the shelf cameras (as shown by the corresponding labels in the images on the right side). The images to the right also show a count of the number of instances of apples, oranges and/or bananas detected before and after the latest interaction. The news-feed shows the inferences made by CheckSoft in response to the hand-based events detected.

As can be seen in Fig. 21, each process on the client machines runs a EventDetector.py program that detects the various events from the video-feed of the corresponding camera and calls the function recordEventSequence(Event) made available through the Blackboard interface. The event recording subroutines are implemented in the VTDRServer.java program that encodes the event information and records it in the EventSeq queue. The encoded event information is then dispatched to the different event handler modules of CheckSoft for further processing.

The video-trackers shown in Fig. 21 are responsible for tracking person instances and their hand movements as well as shelves and the objects present within each shelf to detect events which trigger the different software modules in CheckSoft. Fig. 22 shows the video-trackers detecting human entry and exit events from the video-feed of the overhead cameras installed at the entrance and exit. Fig 23 illustrates the results of person and shelf tracking from the video feed of an overhead camera and the news-feed shows which person is interacting with which shelf. Fig 24
The shelves shown in Fig. 24 contain 3 types of objects – apples, bananas, and oranges. In this simple application, the video-trackers keep track of the number of products of each type present in each of the shelves at any time. The newsfeed shows the hand-based events and the application-specific interaction information between person and objects in the shelves as inferred by CheckSoft. Based on the content information shown before and after the interaction, the reader can verify the operation of CheckSoft for the latest interaction in each of the shelves.

8 Conclusion

CheckSoft is based on several time-honored principles of object-oriented software design [25]. For example, one of the most venerable such principles is that the clients of a software system should only have to program to the public interfaces in the software system. CheckSoft subscribes to this principle by requiring the video tracker clients to only have to be aware of the declaration of the method headers in the Blackboard interface.

Our main goal in this paper was to present a scalable software architecture that can run asynchronously vis-a-vis the video trackers, that incorporates a finite-state machine based reasoning framework for keeping track of concurrent people-object interactions in people-centric spaces. CheckSoft is designed to handle concurrent events simultaneously using a multi-processed event-driven architecture. It is also designed to provide a significant measure of immunity to errors in the event data generated by the video trackers. This is done by enforcing consistency in the finite-state logic between the different events related to the same overall person-object interaction.

CheckSoft has so far been tested with both the simulated video trackers and some simple scenarios involving actual video trackers. That was intentional since all we wanted to accomplish at this stage was to formulate the basic architectural design of the software. Our future work would involve testing CheckSoft in large-scale applications specifically with regards to scalability and tolerance to noise in real-world applications.

References

[1] R. Sarkar and A. Kak, *Scalable event-driven software architecture for the automation of people-centric systems*, US Patent App. 16/436,164, Dec. 2020.

[2] J. Q. Ning, “Component-based software engineering (cbse),” in *Proceedings Fifth International Symposium on Assessment of Software Tools and Technologies*, Jun. 1997, pp. 34–43. DOI: 10.1109/AST.1997.599909

[3] D. L. Parnas, “On the criteria to be used in decomposing systems into modules,” *Commun. ACM*, vol. 15, no. 12, pp. 1053–1058, Dec. 1972, ISSN: 0001-0782. DOI: 10.1145/361598.361623 [Online]. Available: http://doi.acm.org/10.1145/361598.361623

[4] A. Hinze, K. Sachs, and A. Buchmann, “Event-based applications and enabling technologies,” in *Proceedings of the Third ACM International Conference on Distributed Event-Based Systems*, ser. DEBS ’09, Nashville, Tennessee: ACM, 2009, 1:1–1:15, ISBN: 978-1-60558-665-6. DOI: 10.1145/1619258.1619260 [Online]. Available: http://doi.acm.org/10.1145/1619258.1619260

[5] O. Etzion, “Towards an event-driven architecture: An infrastructure for event processing position paper,” in *Rules and Rule Markup Languages for the Semantic Web*, A. Adi, S. Stoutenburg, and S. Tabet, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2005, pp. 1–7, ISBN: 978-3-540-32270-2.

[6] C. Roda, A. Rodríguez, E. Navarro, V. López-Jaquero, and P. González, “Towards an architecture for a scalable and collaborative ami environment,” in *Trends in Practical Applications of Scalable Multi-Agent Systems, the PAAMS Collection*, F. de la Prieta, M. J. Escalona, R. Corchuelo, P. Mathieu, Z. Vale, A. T. Campbell, S. Rossi, E. Adam, M. D. Jiménez-López, E. M. Navarro, and M. N. Moreno, Eds., Cham: Springer International Publishing, 2016, pp. 311–323, ISBN: 978-3-319-40158-7.

[7] M. K. Chandy, *Event-driven applications: Costs, benefits and design approaches*, 2006.

[8] A. Avnur, “Finite state machines for real-time software engineering.” *Computing Control Engineering Journal*, vol. 1, no. 6, pp. 275–278, Nov. 1990, ISSN: 0956-3385. DOI: 10.1049/cce:19900078

[9] F. Wagner, R. Schmuki, T. Wagner, and P. Wolstenholme, *Modeling Software with Finite State Machines*. Boston, MA, USA: Auerbach Publications, 2006, ISBN: 0849380863.

[10] O.-A. Schipor, R.-D. Vatavu, and J. Vanderdonckt, “Euphoria: A scalable, event-driven architecture for designing interactions across heterogeneous devices in smart environments,” *Information and Software Technology*, vol. 109, pp. 43–59, 2019, ISSN: 0950-5849. DOI: https://doi.org/10.1016/j.infsof.2019.01.006 [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0950584919300096

28
[11] R. B. Almeida, V. R. C. Junes, R. da Silva Machado, D. Y. L. da Rosa, L. M. Donato, A. C. Yamin, and A. M. Pernas, “A distributed event-driven architectural model based on situational awareness applied on internet of things,” Information and Software Technology, vol. 111, pp. 144–158, 2019, issn: 0950-5849. Doi: https://doi.org/10.1016/j.infsof.2019.04.001 [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0950584918301137

[12] M. Ben-Ari. Principles of Concurrent and Distributed Programming. Upper Saddle River, NJ, USA: Prentice-Hall, Inc., 1990, isbn: 0-13-711821-X.

[13] R. Vezzani and R. Cucchiara, “Event driven software architecture for multi-camera and distributed surveillance research systems,” in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, Jun. 2010, pp. 1–8. Doi: 10.1109/CVPRW.2010.5543825.

[14] Y. Li, L. Brown, A. Hampapur, M. Lu, A. Senior, and C.-F. Shu, “Ibm smart surveillance system (s3): Event based video surveillance system with an open and extensible framework,” Mach. Vis. Appl., vol. 19, pp. 315–327, Oct. 2008. Doi: 10.1007/s00138-008-0153-z

[15] Z. Wu and R. J. Radke, “Real-time airport security checkpoint surveillance using a camera network,” in 2011 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, Jun. 2011, pp. 25–32. Doi: 10.1109/CVPRW.2011.5981718.

[16] M. Bhargava, C.-C. Chen, M. S. Ryoo, and J. K. Aggarwal, “Detection of abandoned objects in crowded environments,” in 2007 IEEE Conference on Advanced Video and Signal Based Surveillance, Sep. 2007, pp. 271–276. Doi: 10.1109/AVSS.2007.4425322.

[17] E. Frontoni, P. Raspa, A. Mancini, P. Zingaretti, and V. Placidi, “Customers’ activity recognition in intelligent retail environments,” in New Trends in Image Analysis and Processing –ICIAP 2013, A. Petrosino, L. Maddalena, and P. Pala, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 509–516, isbn: 978-3-642-41190-8.

[18] B. Singh, T. K. Marks, M. Jones, O. Tuzel, and M. Shao, “A multi-stream bi-directional recurrent neural network for fine-grained action detection,” in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jun. 2016, pp. 1961–1970. Doi: 10.1109/CVPR.2016.216.

[19] B. Gyori, I. Medrano, A. Frenkel, and P. Java, Shelf with integrated electronics, US Patent 10064502, Sep. 2018.

[20] B. Greaves, M. Coetzee, and W. S. Leung, “Access control requirements for physical spaces protected by virtual perimeters,” in Trust, Privacy and Security in Digital Business, S. Furnell, H. Mouratidis, and G. Pernul, Eds., Cham: Springer International Publishing, 2018, pp. 182–197, isbn: 978-3-319-98385-1.

[21] C. Tsigkanos, L. Pasquale, C. Ghezzi, and B. Nuseibeh, “On the interplay between cyber and physical spaces for adaptive security,” IEEE Transactions on Dependable and Secure Computing, vol. 15, no. 3, pp. 466–480, May 2018, issn: 2160-9209. Doi: 10.1109/TDSC.2016.2599880.

[22] “Java remote method invocation - distributed computing for java, http://www.oracle.com/technetwork/java/javase/tech/index-jsp-138781.html”

[23] M. Fiaz, A. Mahmood, and S. K. Jung, “Tracking noisy targets: A review of recent object tracking approaches,” Corr, vol. abs/1802.03098, 2018. arXiv: 1802.03098 [Online]. Available: http://arxiv.org/abs/1802.03098
A | Tables

| Class   | Attributes | Description |
|---------|------------|-------------|
| Entity  | ID         | This stores an unique identifier for each instance of the different entities. |
|         | PhysicalState | This stores data related to the positional co-ordinates and other physical attributes of the real-world entity. Storing these values is optional in the current implementation, but might be useful in actual systems. |
| Ownership |            | This stores the ownership relations between the different entities, based on the application. It has two lists: `Owns`, where it stores the information for the instances that this instance is the owner of and `OwnedBy`, where it stores the information for the instances that owns this instance. |
| ActionQ |            | This data attribute records all the interaction information for each of the different objects that the human interacted with. It is a hashtable of queues which uses the object instances that the HumEnt interacted with as keys and stores the history of interaction between the HumEnt and each of the objects in separate queues. The interaction information is stored in the temporal order of occurrence. |
| BufferBefore |            | This data attribute is primarily used for temporarily storing the storage content before and after multiple concurrent interactions that the HumEnt instance was involved in, at any particular moment. Multiple such entries are indexed using unique key pairs. |
| ContentBefore |            | This data attribute is primarily used for computation and stores the storage content before and after a particular interaction that the HumEnt instance was involved in. |
| InferenceQ |            | This data attribute records the inferences derived from the history of interaction stored in the ActionQ, between the HumEnt and each of the objects. The inferences are stored for each of the objects in separate queues, in the temporal order of occurrence. |
| ContentAfter |            | This data attribute stores a list of different types of actions that the HumEnt instance can perform, specific to the application. |
| Actions   |            | Each storage entity maintains its own individual content information with the corresponding time-stamp in this data attribute. |
| StoEnt    | Update     | This is a Boolean variable that indicates whether the Content data attribute should be updated or not. This is set to True only if the content information reported by the video trackers is reliable. |
|           | InUse      | This is a Boolean variable that indicates whether the storage entity is currently involved in an interaction. |
| OBlob     | Characteristics | This stores the information related to the characteristics of the object specific to the application. For example, in an airport checkpoint security this could be the classification defining the security threat posed and in a retail store this could store the price of the object for automated billing. |

Table 2: Attributes of the different classes associated with each Entity in CheckSoft

| Class   | Attributes | Description |
|---------|------------|-------------|
| Event   | String     | This is the root class from which child classes for different events are derived. The time-stamp indicating when the event occurred is stored in the attribute Time and the specific event type is stored in the attribute Type. This class has a member function `List<String>encodeEventInfo()` that can encode the information related to the type, time-stamp and the information regarding the entities involved with the specific event in the following format: `[Type, Time, Information regarding Entities involved in the event]` |
| HumanEnter | HumEnt H | This class is associated with the event that a new Human Entity enters the monitored space. |
| HumanExit  | HumEnt H  | This class is associated with the event that an existing Human Entity exits the monitored space. |
| HandIn     | HumEnt H  | This class is associated with the event that any of the hands of an existing Human Entity reaches inside an existing Storage Entity. |
| HandOut    | HumEnt H  | This class is associated with the event that all the hands of an existing Human Entity comes outside an existing Storage Entity. |
| StorageInstantiate | StoEnt S, StoEnt S | This class is associated with the event that a new Storage Entity is instantiated by an existing Human Entity. |
| StorageReturn | StoEnt S, HumEnt H | This class is associated with the event that an existing Storage Entity is returned by an existing Human Entity. |
| StorageUpdate | StoEnt S, List<OBlob>O | This class is associated with the event that new content information is available for an existing Storage Entity. This class has a member function `List<String>parseContentInfo()` that can parse the information related to the different Object Blobs present inside the Storage Entity at any particular moment of time. |

Table 3: Attributes and description of the different classes associated with each Event in CheckSoft
The signature of the `gptwc()` function as follows:

```c
TWC_Out gptwc(Comm comm_name, String oper_type, int p_initiator, int p_target, TWC_Inp inp_obj)
```

In order to understand the signature of `gptwc()`, the reader would find it helpful to also look at the depiction in Figure 25 that shows an initiator process and a target process. The former would also like to send a data object `inp_obj`, of type `TWC_Inp`, to the latter and receive from the latter a result in the form of a data object denoted `out_obj` of type `TWC_Out`.

Revisiting the function signature shown above, the first parameter in the function signature is `comm_name` which must be set to the communicator needed for the two-way communication link. The parameter `oper_type` indicates the specific type of functionality that needs to be executed by the target process. The parameter `p_initiator` is the initiator process rank that requested the two-way communication link. By the same token, the parameter `p_target` is

### Table 4: Functionality of the different Event Handlers

| Event   | Event Handler       | Functionality performed by CheckSoft                                                                 |
|---------|---------------------|-----------------------------------------------------------------------------------------------------|
| Human   | HandleEntity        | Assign an available worker process from the HumEnt_Group. Instantiate an instance derived from the HumEnt class, depending on the application and initialize the instance with an unique ID, update the time of entry \( t_{\text{entry}} \), and initialize the other data attributes. |
| Storage | HandleInstantiate   | Assign an available worker process from the StoEnt_Group. Instantiate an instance derived from the StoEnt class, depending on the application and initialize the instance with an unique ID, update the time of instantiation \( t_{\text{instance}} \), and initialize the other data attributes. If the StoEnt \( S_k \) was instantiated by a HumEnt instance \( H_i \) then update the ownership information in the Ownership list in \( S_k \). Ownership indicating the owner of \( S_k \) is \( H_i \) and the Bloom list in \( H_i \). Ownership indicating \( H_i \) owns \( S_k \). |
| Storage | HandleReturn        | The time of return \( t_{\text{return}} \) is updated and the entity information is permanently recorded. The StoEnt instance \( S_k \) is deleted and the allotted worker process is then freed and made available to the StoEnt_Group. |
| Storage | HandleUpdate        | This event notifies the worker process for StoEnt \( S_k \) that new content information is available from the video trackers and consequently fetches the latest OBlob content from the corresponding Storage_\_csv file and updates it in StoEnt with \( S_k\_\text{Update} = \text{True} \). |
| HandIn  | Interaction Module  | This event triggers the Interaction module (Section 5.3) and the process for HumEnt \( H_i \) fetches the noise-filtered content just before the event, from the process for StoEnt \( S_k \) using a gptwc() function call over the Inter_comm and stores it in \( H_i\_\text{BufferBefore} \). The process for StoEnt \( S_k \) sets \( S_k\_\text{Update} = \text{False} \) to prevent updating the state of \( S_k \) during the interaction. |
| HandOut | Interaction Module  | This event triggers the Interaction module (Section 5.3) and the process for HumEnt \( H_i \) fetches the noise-filtered content just after the event, from the process for StoEnt \( S_k \) using a gptwc() function call over the Inter_comm and stores it in \( H_i\_\text{BufferAfter} \). It then checks for a matching HandIn event and if a matching entry is found in \( H_i\_\text{BufferBefore} \), the elementary interaction information is extracted and then recorded in \( H_i\_\text{ActionQ} \). Subsequently, the Inference module (Section 5.4) is triggered, that analyzes the latest interaction history of the OBlob involved in the interaction and records the inferences made in the \( H_i\_\text{InferenceQ} \). It raises alerts if HumEnt \( H_i \) was involved in any anomalous interactions. The process for StoEnt \( S_k \) sets \( S_k\_\text{Update} = \text{True} \) to allow updates to the state of \( S_k \) after the interaction. |
| Human   | Inference Module    | This event also triggers the Inference module (Section 5.4) that analyses the interaction history with each OBlob in \( H_i\_\text{ActionQ} \) and records the inferences made in the \( H_i\_\text{InferenceQ} \). It raises alerts if HumEnt \( H_i \) was involved in any anomalous interactions. Once all inferences are made, the time of exit \( t_{\text{exit}} \) is updated and the entity information is permanently recorded. The instance is then deleted and the allotted worker process is freed and made available to the HumEnt_Group. |

Figure 25: General Purpose Two Way Communication function

| Initiator Process (p_initiator) | Target Process (p_target) |
|---------------------------------|---------------------------|
| Send input data:               | Fetch Data Computation    |
| MPI Send                        | MPI Recv                  |
| TWC_Inp inp_obj                 | TWC_Out out_obj           |
| Send output data:               |                           |
| MPI Recv                        |                           |
the target process rank that is the other endpoint of the communication link. The parameter `inp_obj` is an instance of the class `TWC_Inp` that has two attributes: (1) `d_input` that is set to the data block being sent by the initiator process to the target process; and (2) `mode` that is used to notify the target process the type of operation it needs to perform as follows:

\[
\text{mode} = \begin{cases} 
0 : & \text{Fetch Data using } d\_input \\
1 : & \text{Compute operation on } d\_input \\
2 : & \text{Fetch using } d\_input \text{ followed by a compute operation}
\end{cases}
\]

The `gptwc()` function returns an instance `out_obj` of the class `TWC_Out` which also has two attributes: (1) `d_output` attribute which is set to the result that the initiator process is expecting from the target process; and (2) `status` that indicates if any errors were encountered when processing the data object sent over by the initiator process. When `status` has a value of 1, that signifies success; other values denote specific types of errors.

### C  Inference Logic for different Applications

#### C.1 Airport Checkpoint Security

The airport checkpoint security deals with distinct and unique objects and each of them are assigned an unique ID. For interactions with each of these objects, there is a temporal relationship between consecutive interactions involving the same person and the same object. To elaborate further, the higher level interactions such as – *Divest object, Move object from bin, Move object to bin, Leave behind object and Collect object* depends on the sequence of two consecutive elementary actions as shown in Table 5.

The `HumEnt` instances own `OBlob` instances and `StoEnt` instances and hence these are the two ownership relationships that are tested by the Anomaly Detector. The first interaction determines whether the `HumEnt` instance divested an item or not and if so, he is Set as the owner of the `OBlob`. The ownership information of the `StoEnt` instances are set before at the time of their instantiation. It can be seen in Table 5 how the Inference module can detect different types of anomalies and can either issue a warning or raise alarms, whenever a non-owner `HumEnt` instance interacts with a `OBlob` and `StoEnt` instance that does not belong to him/her/them.

#### C.2 Automated Retail Store

On the other hand, the automated retail store application deals with multiple objects of the same product type and hence have the same ID. Interactions with a specific type of product can happen in any arbitrary temporal sequence. For example, a `CustEnt` might pick-up 5 items and then return back 2 items and another `CustEnt` can pick up an item one by one and return it one by one. In this application, the higher level interactions such as – *Pick-up item, Return item to correct shelf and Misplace item in wrong shelf* depend only on the latest interaction with an item. This is why the inference module logic for an automated retail store analyzes only the latest interaction with an item instead of a sequence of elementary actions, as shown in Table 6.

The `HumEnt` instances only become owners when they pay at the time of exit. So as long as a `HumEnt` instance is within the store, `StoEnt` instances own the `OBlob` instances and this is the only ownership relationship that is tested by the Anomaly Detector. The ownership information is assumed to be set at the time of installation as it is expected the store will have this information before.

It can be also be seen in Table 6 how the Inference Module can keep track of how many objects were purchased and automatically bill the customer for each product. Further, it can identify when a product is misplaced and notify support staff. Besides, it keeps track of how many times a particular type of product was inspected and returned and how many times a product was actually purchased, and this data can be used by businesses to optimize their operations and build a more efficient inventory management system.

---

11The symbol \( \phi \) in the table represents an empty value (meaning that the next elementary action in the sequence is the first interaction with the object), A and R represent the elementary actions Add and Remove respectively and DNC represents Do Not Care and so it could be either \( \phi \), A or R.

12The symbols A and R represent the elementary actions Add and Remove respectively and DNC represents Do Not Care and so it could be either A or R.
### Table 5: Inference module logic for Airport Checkpoint Security Application.

| Triggered by Event | Latest Sequence of Elementary Actions | Higher Level Interaction | Set/Test Ownership | HumEnt $H_i$ owns OBlob | StoEnt $S_k$ owns OBlob | Tasks |
|--------------------|----------------------------------------|--------------------------|-------------------|-------------------------|-------------------------|-------|
| HandOut            | φ, A                                   | Divest own object $O_j$ in own Bin $S_k$ | Set (OBlob) | $O_j$-Yes | $S_k$-Yes | Append $O_j$ in $H_i$.Ownership |
|                    |                                        | Divest own object $O_j$ in other’s Bin $S_k$ | Test (StoEnt) | $O_j$-Yes | $S_k$-No | Append $O_j$ in $H_i$.Ownership Raise Alarm |
| HandOut            | φ, R                                   | Taking other’s object $O_j$ from other’s Bin $S_k$ | Test | $O_j$-No | $S_k$-No | Raise Alarm |
| HandOut            | R, A                                   | Move own object $O_j$ from own Bin $S_f$ to other Bin $S_t$ | Test | $O_j$-Yes | $S_f$-Yes, $S_t$-Yes | |
|                    |                                        | Move own object $O_j$ from other’s Bin $S_f$ to own Bin $S_t$ | | $O_j$-Yes | $S_f$-No, $S_t$-No | |
|                    |                                        | Move own object $O_j$ from other’s Bin $S_f$ to other’s Bin $S_t$ | | $O_j$-Yes | $S_f$-No, $S_t$-No | Raise Alarm |
|                    |                                        | Move other’s object $O_j$ from own Bin $S_f$ to own Bin $S_t$ | | $O_j$-No | $S_f$-Yes, $S_t$-Yes | Raise Alarm |
|                    |                                        | Move other’s object $O_j$ from own Bin $S_f$ to other’s Bin $S_t$ | | $O_j$-No | $S_f$-Yes, $S_t$-No | Raise Alarm |
|                    |                                        | Move other’s object $O_j$ from other’s Bin $S_f$ to own Bin $S_t$ | | $O_j$-No | $S_f$-No, $S_t$-Yes | Raise Alarm |
|                    |                                        | Move other’s object $O_j$ from other’s Bin $S_f$ to other’s Bin $S_t$ | | $O_j$-No | $S_f$-No, $S_t$-No | |
| HumanExit          | DNC, A                                 | Left own object $O_j$ in own Bin $S_k$ | Test | $O_j$-Yes | $S_k$-Yes | Warn $H_i$ |
|                    |                                        | Left own object $O_j$ in other’s Bin $S_k$ | | $O_j$-Yes | $S_k$-No | Raise Alarm |
| HumanExit          | DNC, R                                 | Collect own object $O_j$ from own Bin $S_k$ | Test | $O_j$-Yes | $S_k$-Yes | |
|                    |                                        | Collect other’s object $O_j$ from other’s Bin $S_k$ | | $O_j$-No | $S_k$-No | Raise Alarm |

### Table 6: Inference Module Logic for Automated Retail Store Application.

| Triggered by Event | Latest Sequence of Elementary Actions | Higher Level Interaction | Set/Test Ownership | StoEnt $S_k$ owns OBlob $O_j$ | Tasks |
|--------------------|----------------------------------------|--------------------------|-------------------|-----------------|-------|
| HandOut            | R                                      | Picked up item $O_j$ from Shelf $S_k$ | Test | Yes | nPurchase++; nInspect++; |
| HandOut            | A                                      | Returned item $O_j$ to correct shelf $S_k$ | Test | Yes | nReturn++; nPurchase--; |
|                    |                                        | Misplaced item $O_j$ in wrong shelf $S_k$ | | No | nMisplace++; nPurchase--; Notify CustEnt and StaffEnt |
| HumanExit          | DNC                                    | *                         | *                 | *              | Add amount for all OBlobs $O_j$ in $H_i$.ActionQ to total bill as : $H_i$.Amount+=[$nPurchase*$O_j.Price] |

Table 5: Inference module logic for Airport Checkpoint Security Application.

Table 6: Inference Module Logic for Automated Retail Store Application.