Occupancy Visualization towards Activity Recognition

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ABSTRACT

We present a sensor visualization system that integrates data streams from individual custom sensor arrays together with Building Automation System (BAS) data. To help bridge the gap between actual building usage by the occupants, and the aggregate assumed usage by the control system, we have developed several sensor processing subsystems moving toward automated human activity recognition without the need for directly instrumenting the occupants. By having a system with a detailed understanding of occupancy behavior and needs, we believe buildings could be much more efficient thereby reducing energy consumption, working toward sustainability of the built environment.

CCS CONCEPTS

• Computing methodologies~ Activity recognition and understanding; • Human-centered computing~ Visualization toolkits • Human-centered computing~ Visual analytics; • Information systems~ Temporal data

KEYWORDS

Visual Analytics; Time-series Data; Human Activity Recognition; Computer Vision

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1 Introduction

As environmental sustainability becomes a global priority, key areas of concern have been collated in the United Nations Sustainable Development Goals (SDGs). In terms of the built environment, Goal 11.c mentions the need for building sustainable and resilient buildings, especially for the least developed countries, so that these nations do not simply follow the actions of the developed world [1]. In the U.S., buildings are the dominant cause of Green-house Gases (GHG) at 2.2 billion metric tons accounting for 40% of American CO_2 emissions [2]. The end use of energy consumption in buildings is primarily space heating (37%), water heating (12%), space cooling (10%), and lighting (9%). As the major factors are all related to the actual usage of the buildings, the gap between the operation of a building and the actual needs of the occupants is a potentially large opportunity for energy and water reduction.

Previous work has shown that occupant behavior can impact building energy consumption up to 23.6 percent [4] based on simulation sensitivity analysis. The frequency and nature of these behaviors has yet to be established and sufficiently modeled. Many techniques exist to detect various activities, such as position [8, 5] and health from gait [6], but none adequately cover the contexts needed for efficient control. To study the potential of sensor fusion in developing novel device-free systems attached to infrastructure (buildings, bridges, etc.), we have created a visualization system that can interactively help researchers discover correlations between systems before investing heavily in programming or machine learning training. By using multiple sensor types with computer vision and combining this with the rich meta-data environment of Building Information Models (BIM), sensors and sensing systems can be evaluated to visualize potential synergies and interactions.

2 Sensor Visualizations

We have developed Dasher360, a web-based sensor visualization tool that displays current sensor values, in the context of building geometry, and can animate historical data for temporal analysis. Implementation of the visualization techniques described in this paper have been done using JavaScript as an extension to Autodesk Forge Viewer [3], a web-based visualization framework to display BIM data.

Figure 1 shows visualization of CO_2 sensors, where sensors are visualized as green sensor dots in 3D space on the BIM. Clicking on a sensor dot opens a 2D plot of CO_2 readings. By having the sensors positioned within the context of the 3D geometry, spatial occupancy patterns in the building can be shown evolving over time as CO_2 levels change, albeit in an abstract indirect way. The

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sensor dot visualization is implemented using a particle system which can render thousands of interactive dots in a layer above the 3D building geometry.

Figure 1: Time-series CO_2 data from BAS sensors.

To further validate CO_2 readings, we visualize CO_2 sensor readings as a spatial heatmap (Figure 2). The heatmap shading uses Shepard's Method [2] to perform multivariate interpolation through a GLSL Shader. The timeline on the bottom of the window can be used to select a time period to play back changes in the heatmap over time. On top of the heatmap, icons of human figures indicate occupant positions based on prototype infrared (IR) sensors developed by Schneider Electric. In the office dataset, we can observe the correlation between higher CO_2 levels with the presence of occupants in the closed meeting room in the bottom left of Figure 2.

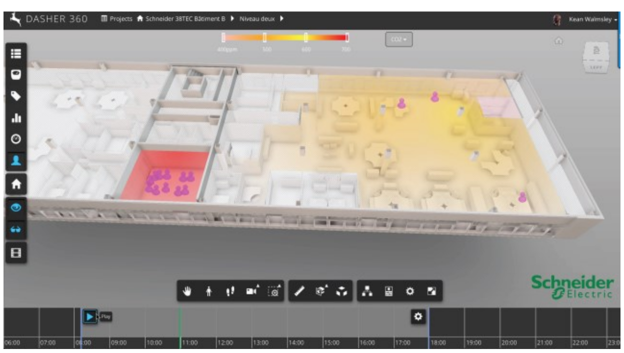

Figure 2: Temperature and CO_2 heatmaps combined with local infrared sensors showing the specific placement of individuals.

In a manufacturing workshop, in addition to CO_2, we instrumented a pedestrian walkway using an array of strain gauges, accelerometers, sound, temperature, humidity, passive infra-red motion (PIR), pressure and ambient light sensors. At both ends of the bridge, we placed video cameras. We processed the video using computer vision to more easily discover when to look for events (occupancy events shown as blue ticks in the timeline in Figure 3), and reference as ground truth.

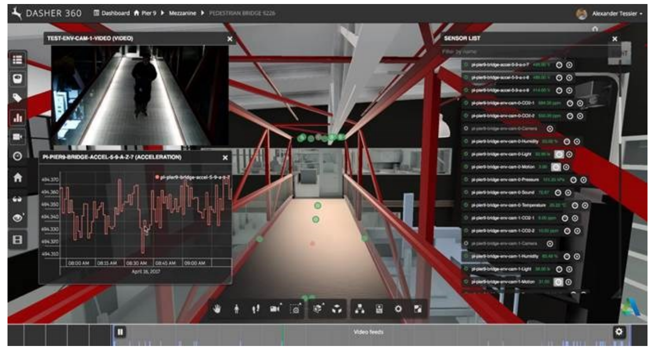

Figure 3: Computer Vision Time-series Tagging.

3 Video Annotations

Our PIR motion detector could only generate data when doors were opened making it necessary to annotate the count of people on the bridge using the video data. To reduce the workload in labeling data, we used a simple Histogram of Oriented Gradients (HOG) [11] human detector and applied it to each image in the video to create a crude occupancy sensor. In this way, we could provide a base-layer of automation for recording when actual occupants were on the bridge in our dataset. This provided a count of people, and a bounding box in the video field (see Figure 4). We then processed this to generate a time-series of human occupancy.

Figure 4: Computer Vision Video Annotation (green outlines on video)

4 Pose Estimation

Human activities and behaviors can be simplified and aggregated into average, schedule-based behaviors as in [4]. However, how these behaviors are affected by specific design features and how those relate back to performance may not correlate well since the details can be lost in the aggregation process [9]. To study these interactions and generate more fine-grained behavioral observations, we employed Pose Estimation [7]. Context specific behaviors, such as pausing in the middle of the bridge to observe surroundings, carrying objects, or walking in groups can only be annotated with poses as in Figure 5.

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Figure 5: Computer Vision Pose Estimation (OpenPose) [7]

By calibrating cameras with markers and using homography, we can map the location of the 2D poses in 3D and provide a relative position of the plane upon which the poses lie within the camera frustum. This positioning provides better spatial context, as seen in Figure 6, and can help determine the load positions of people on the bridge structure. Along with the homography, tracking can be added by classifying heads and following footfalls to create continuous and stable positions for individual poses across frames [10].

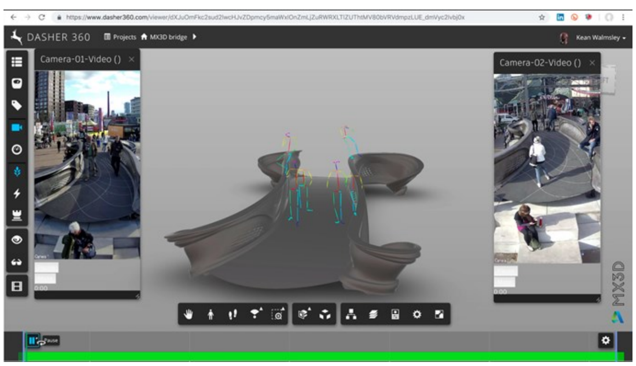

Figure 6: Pose Estimation Streaming into Visualization Tool

As actions can be complex, and group oriented, standard annotation tools and techniques can be extended to create a context aware and relevant labeling system for use in specific situations, such as collaborative interactions in an office environment [9] (see Figure 7). These annotations can be leveraged in supervised machine learning training applications, along with sensor data and on top of pose recognition for context-aware activity recognition. Note that anonymization is supported to some degree by overlaying the extracted stick-figure pose "skeletons" on a 3D model or on a frame of the source video where no people are present.

5 Discussion

By collecting data from a variety of environmental sensors, together with detailed pose information from video sensors, the correlated data sets could provide several benefits. The data can be used for precise indoor positioning together with activity recognition. This, in turn, can be used for (a) precision HVAC and lighting control increasing building performance, and (b) human safety and security in both normal and emergency scenarios. The former use case will be critical in low-energy or net-zero buildings [12] where maximal efficiency is needed continuously both to meet the immediate needs as well as conserve resources for use over seasonal periods.

Uniquely, this work positions the sensed data in the context of a Building Information Model. This extra information adds enough context to make the data meaningful to the observer. Also, this work focusses on making the data directly accessible through visualization, supporting a data-driven exploratory analysis process, rather than providing information that has been aggregated in space and/or time. This is a critical point as this process can help form new hypotheses rather than only confirming the existence of features.

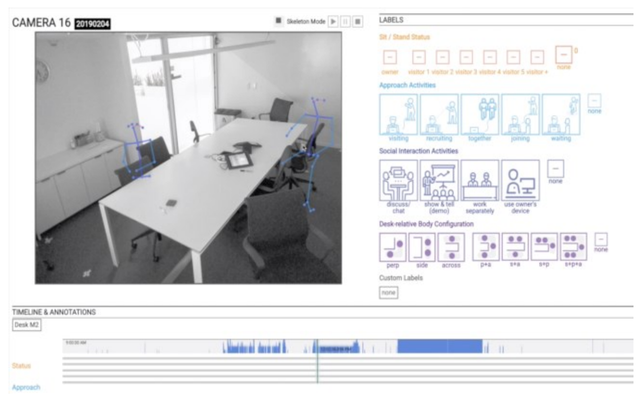

Figure 7: Skeleton-based video annotation system [9]

6 Conclusion and Future Work

The work presented has spanned multiple projects over several years, working towards a more precise, complex, yet automated understanding of occupancy in buildings. The key contribution of this work is to present a comprehensive visual analytics system that can interactively help researchers validate and understand various raw sensing data in context of BIM, prior to any aggregation. By connecting multiple visual analytics methods, we believe this work will form a solid foundation to support the development and validation of equally precise simulation models that can help to create highly efficient model-based controls as well as design tools for architects and engineers to develop buildings that do not generate any greenhouse gases.

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