Summary of the administrative activities in the 4th quarter:

- Based on the request from Intel Taiwan and Taiwan NSC, our team is currently exploring the possibility of applying for NSC 产学合作研究計畫. This is one possible continuation of the Intel digital health project. Specifically, Intel Taiwan would like NTU to find a third working partner. We have identified a few possible candidates, such as Quanta, BenQ, etc. Our first stop was Quanta, which it has closed tie with NTU. So about 4 weeks ago, we went to Quanta to present our research proposal, and it is followed with efforts and exchanges to try to identify some common interests. However, at this point of time, we have not received a definite-go response from Quanta. In other words, it is likely that Quanta may not be interested in this type of research collaboration. We hope that Quanta can give us an answer soon, so that in case this collaboration does not work out, we may explore opportunities with other companies. We would like Intel Taiwan to know that we are putting efforts into this, and we will update Intel Taiwan with our current progress. In addition, we also hope that Intel Taiwan will continue to support the 2nd year of this project.

Summary of the research activities: we have a lot of exciting activities to report!

- **Demo scenario (interactive care wall):** In this quarter, we have redesigned the hardware structure of the steerable projector. The original design of our steerable projector is show in figure 1(a). The original design has two main drawbacks: First, the steerable projector suspended vertically to the ceiling would occupy more space below the ceiling. Second, obstructed by itself, the steerable projector cannot project images right underneath it on the floor. This limits the applications of the steerable projector. To improve the system, we proposed the new design, as shown in the figure 1(b), which moved the steerable projector to the space above the ceiling, and avoid the interference with other projectors.

  To facilitate the control of the iCare wall, we have integrated it with orientation-aware hand-held devices. In our NSC research project, we have found location- and orientation-aware hand-held devices have high potential to be used for interacting with large displays at home or in public. To interact with the iCare wall, we treat the hand-held device as a touchpad to control the mouse cursor or to move the high-resolution projection on the iCare wall. The user moves the mouse cursor by simply dragging the stylus on the PDA. While perceiving 3D models on the large display, the orientation-aware handhelds can also provide the users an intuitive way to manipulate the 3D model.

  Besides, the device can also provide an intuitive user interface for interacting with the physical environment. As shown in the figure 2, a panorama of the environment built in advance is displayed on the handheld device for the user to align the panoramic views with the real world. Through the panorama-based selection scheme, one can interact with, or retrieve information of, an object seen in the 3D environment in a natural and intuitive way. With our hand-held device, the elder can easily access the electronic appliances at home.
Figure 1. (a) Original Design of Steerable Projector; (b) The new prototype of steerable projector

Figure 2. The panorama of the environment is displayed on the handheld device.

- **Infrastructure (subprojects #1):** During this quarter, we have completed two sensor network infrastructural testbeds. The first testbed is a 15-node deployment in the NTU CSIE department building. Each sensor node is a NTU Taroko mote, containing a Zigbee radio, an embedded processor, and open ports for interconnecting sensors. The floor layout of the NTU CSIE testbed environment and the sensor node placements are shown in Figure 3. To show that this infrastructure works, we have created an application – an indoor localization system (subprojects #2 & #3). This indoor localization system is composed of infrastructure and mobile components. The infrastructure component consists of beacon nodes installed on the ceiling of the deployed environment described previously. These beacon nodes are NTU Taroko motes shown in Figure 4. These beacon nodes use Zigbee radio to periodically broadcast beacon packets containing their beacon-IDs. The mobile component consists of MicaZ motes also shown in Figure 4, carried as badges by tracked persons. Each MicaZ mote has the same Zigbee radio as in the infrastructure component.

Each MicaZ mote can take out receiving power of beacon packets and relay (beacon-id, signal-strength) pairs back to our positioning engine running on a remote server though a sensor network infrastructure. This positioning engine was developed previously in our lab. It runs a hybrid algorithm combining signal strength (SS) fingerprint and SS propagation model. Once the positioning engine collects enough signal strength (SS) information from a mobile badge, it estimates the badge’s current position. The current position is forwarded to a location middleware, which then reports the current position to the application.

The resulting positional accuracy has been promising – the error seldom goes beyond 3 meters. This level of accuracy is sufficient for tracking people at home.
Indoor localization (subproject #2 & #3): We have completed the first stage of our energy-saving enhancement for the ZigBee based indoor localization system described in the previous page. We are designed and implemented a sensor-assisted method for energy saving. That method incorporates an accelerometer sensor on a mobile Zigbee unit carried by a person. The accelerometer sensor can detect the human movement level. When the amount of movement is small (e.g., a person sitting on a sofa or sleeping on a bed), the sampling rate of location tracking can be significantly reduced to save battery on the mobile Zigbee unit. More specifically, our energy-saving methods (1) enable an application to specify an error tolerance requirement and then (2) dynamically adapt the sampling rate for quasi-optimal energy saving while meeting the application’s error tolerance requirement.

We have also tested our implementation in our sensor infrastructure – a real working environment (subproject #1). We have found that our proposed energy-saving method can produce energy saving by a significant margin of 49.76% at the 10% (low) mobility level. Mobility level is measured as a percentage of time when a user is moving vs. remaining static. This energy saving benefit decreases to 6.88% at the 90% (high) mobility level. Note that in most indoor environments (e.g., offices or home), people don’t move too much in the indoor environment; in other words, 10% mobility level is typical.

Indoor localization (subproject #2 & #3): Based on our prior tracking techniques
(single camera and smart sensory floor), we have developed a more robust tracking system by integrating four CCD-cameras and our smart sensory floor to track multiple elders simultaneously in a cluttered environment. The system also exploited a Bayesian-Filter based data fusion technique in the integration of non-commensurate sensor data (video and load sensory data) in order to robustly determine or predict elders’ locations. At first, the system applies an enhanced particle-filtering-based algorithm along with a clustering mechanism (agglomerative hierarchical clustering) to identify multiple targets from different video streams and load sensory blocks. The system then reckons two key indexes which represent both the reliability of each sensor and the quality of every observation; that is, these indexes represent the current trustworthiness of cameras and load sensory sensors and can be used to determine their weights while fusing different sensor inputs. Finally, we also designed several testing scenarios to demonstrate the effectiveness and the robustness of this enhanced system. The experimental results show that the enhanced system can outperform the single sensor system by up to approximately 20% in the error distance comparison.

![Multi-camera tracking system](image)

**Figure 5. Multi-camera tracking system**

- **Activity Inference (subproject #4):** we have created a wearable RFID sensor device for our activity inference. This activity inference system works as follows. By attaching cheap, readily available, passive RFID tags on everyday objects and embedding tiny, mobile RFID readers on a person’s wearable such as a finger-ring or a wrist-watch, the smart environment can unobtrusively monitor human interactions with these RFID-tagged objects in the physical space. By monitoring these person-object interactions and tracking people’s indoor locations (subproject #2 & #3), the inference engine can infer high-level safety-related activity context, such as a person who turns on a stove in the kitchen (touching the stove knob) and then walks away for a long time (he/she may forget to turn off the stove), a person who opens a window and then leaves home (he/she may be in a risk of burglary), a left-along toddler who holds small items (such as coins, buttons, marbles, beads) and is in high risk of choking on them, etc.

  Our system works by embedding a tiny RFID antenna and a RFID reader into a wearable finger-ring (shown in Figure 6) and a wrist-band (shown in Figure 7), enabling them to sense any RFID-tagged objects being physically touched by our hands. Location tracking of RFID-tagged items is done in conjunction with ultrasonic-based Cricket location tracking system. It also includes a small RFID middleware that maintains mappings between RFID code words and RFID-tagged
items, as well as last seen locations of these RFID-tagged objects.

We have identified the following activities for inference: dressing, washing cloth, making phone calls, playing music, toileting, washing hands, brushing teeth, making and drinking tea, eating medications, etc. We use Hidden Markov Model (HMM) as our basic activity model to achieve efficient inference. Our experience with HMM have found the following confounding factors. “The activities that the user performed shared objects in common. This made interleaved activity recognition much more difficult than associating a characteristic object with an activity (such as a vacuum)”. Therefore, we design a Filter-Enhanced HMM to solve this problem. And In our experiment, our new model can improve the accuracy from 56% to 88%.

Figure 6. The RFID wristband containing a RFID reader and a NTU Taroko mote

Figure 7. The RFID antenna finger ring without decoration and with decoration

Activity Inference (subproject #4): Human Pose–based Accident Detection -
Human pose estimation is an important and challenging topic for a wide range of video understanding applications, such as human-machine interaction, security surveillance, and accident detection, etc. The challenges in this problem are mainly due to appearance variations which include clothing, self-occlusion, and articulated-deformation. The approaches in this area can be divided into three classes depending on the methodologies used for pose estimation. More specifically, the classes for categorizing the pose estimation approaches are component-based approach, template-based approach, and parameterization-based approach. We are developing a system to recover an elder’s current posture by applying a pose parameterization-based approach. In the current phase, the 2D human model we adopt is composed of ten body parts and nine joints as shown in Figure 2. Although our proposed approach is time-consuming for the time being since the solution space (all possible combinations of a human body) is always multi-modal and high-dimensional, it is more effective and more general than the other two commonly used approaches (component-based approach and template-based approach). The key issue is how to effectively obtain the most likely posture while searching in the solution space. That’s why we are now focusing on proposing a more efficient searching method for the pose parameterization-based approach. We can then utilize this solution to recover an elder’s pose even when some body parts
are occluded or skin color of limbs is invisible; furthermore, the system can analyze a sequence of elders’ poses to detect if a falling or tripping accident has occurred and then automatically inform caregivers as soon as possible.

Summary of the research results: we categorize our results into two parts. The first part is video. We strongly believe in video – video is worth more than many thousand words. We also believe that good technology should also demonstrate not only what they are but how they can be used in our everyday lives. For technical details, the 2nd part covers our publications.

Video URLs:

- Smart floor tracking: [http://robotlab.csie.ntu.edu.tw/H/Demo/smart_floor_demo.avi](http://robotlab.csie.ntu.edu.tw/H/Demo/smart_floor_demo.avi)
- Persuasive lunch tray: [http://mll.csie.ntu.edu.tw/video/game.avi](http://mll.csie.ntu.edu.tw/video/game.avi)

Publications:


Kenji Okuda, Shun-yuan Yeh, Chon-in Wu, Keng-hao Chang, Hao-hua Chu, “The

