

Human Activity Inference via physical sensing in support of Industrial Equipment Maintenance

Michael J. McGrath¹, Joe M. Bulter¹, Adam Rae² and Stephen Hughes³

¹ IT Research, Intel Ireland, Leixlip,
Co. Kildare, Ireland
{Michael.J.McGrath, Joe.M.Bulter}@intel.com

² Intel Research, Seattle, USA
{Adam.Rae}@intel.com

³ SAMH Engineering,
1 Leopardstown Drive, Blackrock
Co. Dublin, Ireland
{stephenahughes}@gmail.com

Abstract. The paper describes an active research project at Intel's High Volume Manufacturing (HVM) facility located at Leixlip, Co. Kildare, Ireland. The project explores the practical aspects of deploying RFID transponders, subtle sensing platforms and machine learning based inferencing in a harsh, real-world environment. The key features of the sensing platform, the data collection process and the translation of data into information using visualization and inferencing techniques are described.

1 Introduction

With ever increasing pressures to optimize factory performance, the area of high precision maintenance has fallen sharply into focus. As the complexity of process equipment increases with new technology revisions, so has the complexity of equipment maintenance. Increasingly detailed textual information creates issues of cognitive overload for equipment technicians which can have a detrimental effect on the quality and the expedience of maintenance activities. Faced with a real business need a research project at Intel's high volume facility located in Leixlip, Ireland by IT Research in collaboration with Intel Research is exploring the viability of activity inference to support equipment maintenance execution within a clean-room environment. The specific goal of this project is to build a system that can automatically infer a wide range of everyday human activities and provide proactive assistance, if needed, to complete an activity [1], [2]. Key elements of the physical context i.e. the equipment and surrounding environment are labeled with RFID tags, which are read via a discrete bracelet-encapsulated tag reader, based on the technician's proximity to the element in question. This generates a signal / record of the technician's interaction with equipment and surrounding environment during the PM (preventative maintenance) activity. The recorded data is then fed to inferencing software that decodes and

categorizes the activities and provides a meaningful visualization of the activities executed during the PM.

RFID tags and readers provide a simple, robust sensor stack for object-person interactions. This application reverses the typical role of the RFID reader and transponders, by equipping the user with the reader and fixing the RFID transponders. High Frequency (13.56MHz) passive transponders are utilized, providing a maintenance free tagging solution once the transponders are affixed.

This project explores the practical aspects of deploying RFID transponders, subtle sensing platforms and machine learning based inferencing in a harsh, real-world environment.

2 iBracelet

The tags IDs are read via an iBracelet when the technician is in proximity to the tag. This provides a record of the technician's interaction with the equipment and surround environment during the PM activity. The bracelet is worn over the user's wrist and beneath the full-body Gore-Tex® suit worn the clean-room environment to prevent particle contamination.



Fig. 1. iBracelet Form Factor

The iBracelet comprises a custom designed RFID reader / antenna, a wireless communication module (the Crossbow® MICA2DOT Mote), a Li-ion battery and charging circuit, all encapsulated within one of two sizes of a bracelet-like enclosure. The miniature RFID reader supports a sub-set of the ISO15693 protocol. The reader was designed to maximize both battery life and read range while keeping the weight to a minimum (so as to limit the burden on the users). It works by regularly querying for transponders that may be in range, using the ISO15693 inventory request command, and storing the time and Tag-IDs of any transponders that respond in local memory. The scan frequency can be adjusted, with a minimum of 1 scan per second and a maximum of 16 per second. The default is set to 8 scans per second. Physically, the RFID

reader component of the iBracelet is 25mm in diameter, with power and communication connections aligned for stacking with the Mica2dot. The design features a number of energy saving techniques which allow the iBracelet to run for up to 150 hours between charges. The RFID reader circuit was also designed to be highly efficient and it achieves read ranges up to 350mm depending on the type of transponder used.

3.0 RFID Transponders

A variety of RFID commercially available transponder form factors have been investigated including credit card, laundry tag and adhesive labels. Each exhibited varying degrees of sensitivity depending on the contact surface. All of the form factors demonstrate extremely poor performance on flat metal surfaces, which are found in abundance within the clean-room environment. The main factor in the loss of read range is due to detuning of the transponders resonant frequency and hysteresis/eddy current losses in the metallic objects that the transponder is in proximity to. Initially plastic spacers were used to reduce these effects; however the disadvantage of this approach is the increase in the physical size of the transponders making them obtrusive when installed. Commercially available transponders designed specifically for metal surface contact were also investigated. These exhibited extremely poor sensitivity and were much less sensitive than standard transponders, as a result of hysteresis losses due to the high permeability of their construction materials. The final compromise was to design in-house 'tunable' transponders, which delivered a doubling of read range for the same height of transponder over the commercially available 'fixed' types of transponder. Read ranges of 270 mm were achieved in combination with a 25 mm plastic spacer on large solid stainless steel surfaces. These 'tunable' transponders were installed on selected areas of the process tool such as the tool frame.

A potential drawback of using RFID as the sensing platform is the potential for the iBracelet to read more than one transponder id during a given activity. With this issue in mind the locations and the transponder types have been carefully selected to prevent overlapping thus negating the need for data filtering.

4.0 Data Labeling

Machine learning is a key aspect of the activity inference project. For a system to automatically infer what activity is being performed, it must have a detailed model of the activity. Specifically, the system must have the following information: a text label for the activity; the number of steps involved; the objects used in each step, and the probability of using them; and the estimated time it takes to complete each step. This allows the software to act as a classifier of a given activity.

The initial starting point for this activity has been the process of transposing standard maintenance checklists into activity sequences based on a known set of physical interactions within defined time segments for key blocks of the PM activity. The expected activity based on the specified sequence of the PM is assigned the highest weighting.

Activities which are located on a temporal basis to the primary activity are assigned lower weightings. This process is repeated through the sequence of actions of the PM activity. The difficulty in developing models for the PM activity is the resolution of the data. Many parts of the tool are impractical to label due to thermal or RF considerations. Development of robust models which can accommodate sequences of poor data resolution is an on-going effort.

5.0 Visualization, Inferencing and Machine Learning

The information which is collected during a PM activity is downloaded via a wireless communication module from the iBracelet's flash memory to a host PC. This information can be displayed as a time series graph using a visualization application which has been developed by Intel Research as shown in Figure 2.

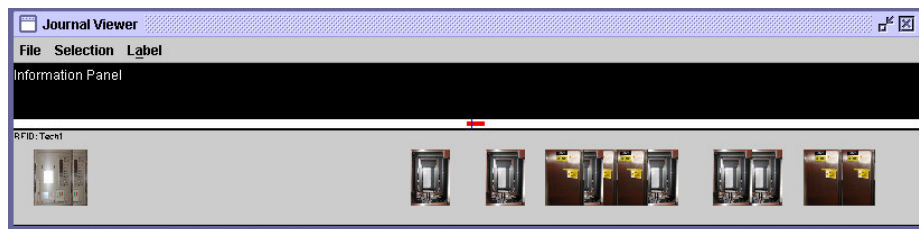


Fig. 2. Data visualizer showing the early stages of a typical high precision activity on a semiconductor process tool.

Each unique tag id is associated with graphical icon which corresponds to the tagged physical item. The visualization engine allows the process engineer to replay the key activities of the PM. This capability allows the engineer to examine if the PM was carried out in the expected sequence. If deviations are identified, they can highlight a lack of proficiency due to incomplete training of the technicians. More interestingly, they can also highlight optimizations of the PM activity which have evolved through tribal knowledge but have never been formally identified or captured. Timing information can be overlaid with the graphical information which allows the engineer to determine performance against the target time for each segment of the PM. Reliable information at this level of granularity is not available through current Shop Floor Control (SFC) systems. PM sequences which have not achieved their target time performances can be analyzed and corrective actions to improve performance added to the PM. This will allow process engineers to identify opportunities to improve PM performance and to provide a platform to measure the effectiveness of incremental improvements. Initial data sets have indicated that out of order activities are occurring due to local optimizations.

The data can also be made available to a reasoning engine - a machine learning algorithm that analyzes the data, compares it to a large set of activity models, and infers which model is the best match. The mechanics of the reasoning engine which was developed by Intel Research has been previously described [1], [2], [3]. Development of

appropriate models are currently at an early stage. The key benefit of these models is that appropriate contextual information from the checklist to support that activity can be presented to the technician based on the prior identification of a given activity during the PM. This helps to reduce the cognitive workload for the technician allowing them to concentration on the quality and effectiveness of the PM rather than expending time and cognitive resources finding and processing the correct information. This capability forms the cornerstone of real personalized computing capabilities.

6.0 Key Challenges

The project addresses practical challenges in a number of key areas. At the physical level, transponder reading performance, with tags mounted on metal structures proved problematic, and some customizations of the tag circuitry were required to obtain satisfactory results. Power management, radio performance and data storage efficiency were critical issues in the design of the bracelet-based reader, requiring development at both the circuit and firmware levels. Achieving activity inference through classifier techniques and sensor trace visualizers, with reference to activity definitions, requires translation of structured knowledge (specifications) into tractable models. The PM usage model has highlighted issues regarding data resolution which results from inherent limitations present in a HVM environment. These limitations must be addressed in the development of robust activity models for PM activities.

7.0 Conclusions

This project has addressed some of the practical issues of using RFID transponders, subtle sensing platforms and machine learning based inferencing in a HVM environment. The information collected is delivering improved visibility on PM activities on semiconductor process tools. The development of models to support inferencing modeling is currently on going.

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