Working Process Quantification in Factory Using Wearable Sensor Device and Ontology-Based Stream Data Processing

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Abstract. A method for quantifying working processes on manufacturing floors was established that uses a wearable sensor device and an ontology-based stream data processing system. Using this method, the measurement of manufacturing process efficiency from sensor data extracted from such a device worn by workers on the job was confirmed at the Fuji Xerox factory.

Keywords: Ontology, Stream data processing, Wearable device, IOT

1 Introduction

A real-time understanding of the situation at production sites is essential for management in manufacturing companies. Their ability to exploit unstructured as well as structured knowledge in the production field determines their manufacturing competitiveness. Knowledge in the production field includes three factors: production machinery, productive resources, and humans engaged in production. The machinery and resource factors, which are easy to measure quantitatively and can therefore be projected onto structured data, have been thoroughly utilized in manufacturing management. In contrast, the human factor, which is unstructured and therefore difficult to sense, has been little utilized so far.

The purpose of this study is to establish a method for quantifying the human factor on manufacturing floors. We first propose to monitor factory job processes with wearable sensor devices. The meanings of signals detected by such devices, however, are not uniquely determined; that is, the same signals detected in different contexts can have different meanings. To define the meaning of each detected signal uniquely in each context, we further propose to exploit ontology-based complex modeling.

2 Related Work

Kharlamov et al. [1] have advocated ontology-based data access (OBDA) as a suitable Web-driven technology for effective and efficient access to data accumulated in production fields. Their approach has focused on the machinery and resource factors but has not been able to address the human factor.

Real-time data addressing is achieved by a data stream management system (DSMS) or a complex event processing (CEP) system [2]. These can address large datasets, reactivity, and fine-grained information access, but they cannot make complex application domains model heterogeneous data. Stream reasoning technology can solve this problem [2]. However, a trade-off exists between the complexity of the reasoning method and the frequency of the data stream of the reasoner. Morph-streams [3] can ease this trade-off using ontology-based reasoning and the rewriting of queries using the CEP/DSMS query method. A barrier to the introduction of Morph-streams is that they require well-understood operational semantics for DSMS and CEP.

3 Approach

Wearable sensor devices were used and optimized to correspond to human activity specific to the production field. In order to reduce the barrier to introduction, a CEP system for semantically filtering stream data was implemented.

3.1 Wearable Device Optimization

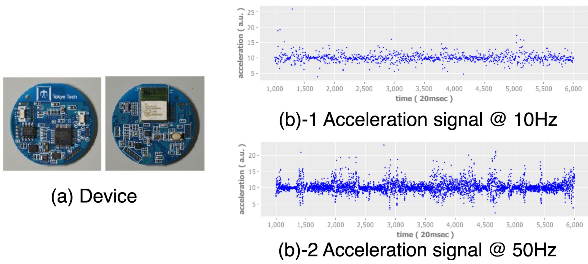

Fig. 1. Wearable sensor device and sensed signal

Fig 1(a) shows the wearable sensor device used in this study. The device was developed by LAPIS Semiconductor in the HAPIC project [4] and is designed to detect human movements of daily living using 10 types of sensors, such as a three-axis acceleration sensor, a three-axis gyro sensor, a three-axis geomagnetic sensor, and a barometric pressure sensor.

The character of motion in a factory work process differs greatly from that in daily living because factory work requires more effective motion for mass production. Fig 1(b) shows the acceleration sensor signal for a factory job process at different sensing frequencies (10 Hz and 50 Hz). For daily living, 10 Hz is the parameter value, whereas 50 Hz is the parameter value optimized for this work. This result shows that the daily living sensing frequency cannot detect the operations of factory workers. The 50-Hz frequency requires a higher communication bandwidth, but there is a trade-off between high communication bandwidth and battery management. We resolve this conflict to optimize the communication data profile, device profile, and system profile.

3.2 Ontology-Based Stream Data Processing

There are many workers (more than several thousand) and a wide variety of job processes (more than several hundred) on the production floor. State control of such huge and complex events is difficult with a conventional DSMS/CEP module. We propose a method for semantically filtering stream data to reduce such complexity. Fig 2 shows the architecture of our system. Sensed data are collected in the sensor/actuator control hub and transferred to Key-Value stream data. Key data are created from the time stamp and the device address using RFC4122, and Value data are created from the sensed raw data. Stream data corresponding to reactivity and scalability are stored in the Key-Value Database (KVDB). The service module semantically filters the stream data from the KVDB using ontology-based reasoning and query rewriting to key select queries. The reduced quantity of stream data can be accessed by a simple CEP module such as embedded event processing (eep). The CEP module has pre-processing submodules such as a low path filter, feature extraction submodules such as a fast Fourier transform (FFT), classification submodules such as a hidden Markov model (HMM), and post-processing submodules.

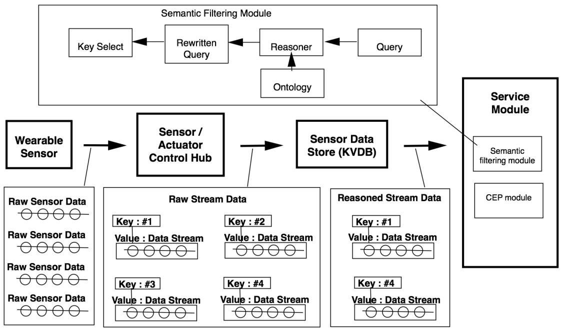

Fig. 2. Ontology-based stream data processing system

3.3 Ontology

In order to address the working process context for the sensed data, we created a manufacturing ontology from the operation instruction manual (OIM), which describes in detail the assembly motions, procedures, and related parts information. The manufacturing ontology consists of the basic motions, procedures, and product component ontology. Manufacturing context reasoning was produced to match the basic motion ontology to the classified sensed data.

4 Scenario and Results

Many factory workers in Japan have performed an improvement activity called Kaizen. Conventional Kaizen begins with a working process quantification that is carried out via job analysis and process time measurements. The working process quantification requires much time and a high level of skill because the job analysis requires a deep knowledge of work processes.

We assume a simple scenario for real-time manufacturing process quantification as follows: An assembly worker puts the wearable sensor device on his or her wrist and collects job process data with it. The manufacturing engineer select the job to improve. System shows directly selected job process efficiency value (activity efficiency, motion efficiency) and standard value. If job effiency value differ widely from standard value, they go to improvement process.

We examined the above scenario in the Fuji Xerox Printer assembly line. The manufacturing engineer queried the job and collected the data, which were filtered using queries rewritten from it. The filtered data components such as acceleration, gyro, and geomagnetic data were then used to calculate the direction and magnitude of displacement that occurred during the job process. Activity efficiency (derived from integrating the magnitude of displacement) and motion efficiency (derived from the anisotropic ratio of the direction) were able to be viewed in real time and compared to standard one.

Table 1 shows activity efficiency and motion efficiency value at different production lot compared to standard one. This result shows big activity efficiency dispersion is exist in the job, and that indicate the job process containes redundant motion and needs to improve it.

Table 1. Manufacturing process quantification results

indicator	job@1st-production-lot	job@2nd-production-lot	job@Standard
activity efficiency	58.7	131	100
motion efficiency (%)	55	44	58

5 Conclusion

We confirmed that our method can be used for quantification of a manufacturing process in Fuji Xerox. Our system allows real-time manufacturing process improvement using human factor information, which has not been satisfactorily utilized to date. Our next step will be to apply it in other scenarios such as the creation of links between process quantification data and enterprise data.

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