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Sensor Data Based Models for Workforce Management in Smart Manufacturing

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Abstract

Manufacturers conduct frequent product innovations to maintain their competence in the market. Accordingly, their workers need to upgrade skills and regain work efficiency in ever-changing manufacturing systems. Training and assisting workers on their job serve this purpose. Yet, their effectiveness relies on an understanding of workers' needs, their operational behavior, performance, and sometimes the prediction of these. This paper aims to discover the unique capability of workforce management in smart manufacturing (SM) where advanced sensor technologies and machine learning techniques are commonly implemented. The paper summarizes technologies for sensing workers in their workplace. Then, it shows that the sensed temporal-spatial data of workforce, after being processed, can be used to infer and model substantial worker information such as location, configuration, motion, and action. Provided these models, SM is able to assist and train manufacturing workforce in a precise and proactive manner. The paper demonstrates the implementation of the proposed models with a practical manufacturing operation. It also summarizes management implications of the models.

Keywords
Smart manufacturing, workforce management, worker activities, performance measurement, temporal-spatial data

1. Introduction

The modern human society is undergoing a fast changing life. They are passionate about cutting-edge technologies and neoteric products. Consequently, traditional manufacturing systems need to harmonize with the changing pattern of consumer affinities [1]. To address the issue, smart manufacturing (SM) is emerging as integrated and collaborative manufacturing systems, to deliver competitive products in response to ever-changing customer needs.

Apart from incorporating state of the art technologies like cyber-physical production systems, internet of things, automation, big data analytics, and cloud computing into manufacturing systems, SM also emphasizes on agile and skilled workforce [2]. Moreover, assembly systems are transforming from a mass production scheme to mass customization scheme in the modern realm of market fluctuations. Therefore, for effective implementation of advanced manufacturing techniques, resourceful workforce is indispensable [3]. Undeniably, in the process of making the workforce resourceful, it's imperative to capture sufficient data pertaining to worker activities from the workplace to derive an optimal solution of training and assistance in a near real-time manner. Embedded with multitude sensors and actuators, SM provides the opportunity to make that happen. Different types of sensors can be utilized based on the requirement of data. Processed sensor data can be used to develop quantitative models to comprehend workforce information like location, configuration, motion, action, and so on. This paper is motivated to explore this new opportunity of workforce management.

The remainder of the paper is organized in the following. Section 2 summarizes sensing technologies that can be used in SM to obtain workforce data. Temporal-spatial models of worker activities are proposed in Section 3, which can be parameterized using the sensed data. To demonstrate the implementation of the models, Section 4 presents an example pertaining to real life manufacturing operations. The paper concludes in Section 5 with a discussion of engineering management implications of the proposed models.

2. Sensor Technologies for Monitoring Workers

Being equipped with various sensors, SM provides the opportunity to collect diverse data of worker activities in the workplace. These sensors could be roughly organized in three categories, as following.

2.1 Radio-Frequency Identification (RFID) Sensors

The Radio-Frequency Identification (RFID) is a wireless communication technology that can be used for identifying, locating, and tracking entities including workers in their working environments. An RFID system consists of three devices: a tag attached to the entity to be tracked, a reader, and a middleware software. The tag stores encoded data and responds to queries from a reader. The reader reads the data and sends to the software. The software deciphers information pertaining to the entity in an explicit form and passes it to an information system for further use. Wireless, contactless, economical, non line-of-sight readability, and unobtrusiveness have expedited its wide range of applications including recognition of human motion, posture, gesture, and action [4]. Yet RFID usually requires a large number of space and infrastructures for installing more readers for higher precision and accuracy.

2.2 Vision Based Sensors

Vision based sensors include various types of cameras (depth, color, and infrared) that can capture videos of worker activities in the working environment. The recognition of such activities from the captured videos has been a focus of extensive research in the computer vision [5]. By processing the videos, relevant features are extracted. A model is then trained using extracted features and known corresponding activities to develop an algorithm of activity recognition. Given a sequence of images or a video, the algorithm can estimate the activity performed by the worker. Vision based sensors are capable of collecting huge data with less set up. Nevertheless, occlusion and proper positioning of cameras are among the challenges in implementing these sensors.

2.3 Wearable Sensors

Wearable sensors are attached with the worker to be sensed and monitored. Commonly used wearable sensors include accelerometer (measuring acceleration and directions), gyroscope (measuring angular velocities), and electromyography (measuring muscle tension changes) sensors. The accelerations, angular velocities, and muscle tension get changed as workers perform assorted activities, which are captured by these sensors. The sensor data are processed and analyzed for recognizing worker activities [6]. Wearable sensing can address the occlusion, positioning, and viewpoint limitation challenges of other sensor types. However, wearing sensors during operation could be inconvenient and troublesome.

Each type of sensors has a unique capability in collecting certain data about workers. Sensor fusion that involves using multiple types of sensors will enhance the ability to collect comprehensive, multi-scale data of manufacturing workers.

3. Temporal-Spatial Models of Workers

Processed and analyzed sensor data of workers in the workplace provide the following four categories of temporal-spatial information about them.

3.1 Location

The location of a point on a worker (such as a body joint) at a time is captured by its position in a location measurement space at that time. Sensors identify the point and provide its coordinates in the measurement space. Let t be a sampling time of sensors, the location of the body point in the three-dimensional measurement space at time t is

$$l_t = [\ x_t \quad y_t \quad z_t\ ]. \tag{1}$$

3.2 Configuration

The human body or a body part (such as the limb, hands, head, face, and so on) can make multiple (static) configurations. Body postures, hand gestures, and face expressions are representative examples of configurations. We can infer worker activities and emotions from their configurations.

Recognition of a configuration requires multiple body points on the worker, such as body joints [7, 8] . Let N_C denote the total number of points of a configuration, indexed by j. $J = \{1, 2, \dots, N_C\}$ is the index set of these points. Then, the spatial model of the configuration at time t is the sensed location data of these points:

$$L_t = \{l_{j,t} : j \in J\}. \tag{2}$$

The data in (2) can be used for training configuration recognition algorithms. Given a trained algorithm, the data can also be input into the algorithm to identify the corresponding configuration. The spatial model in (2) builds a foundation for studying motion and action to be discussed.

If workers commonly use some typical configurations in performing a task, these configurations can be defined for various uses. Let N_K be the total number of these configurations, indexed by k. $K = \{1, 2, \dots, N_K\}$ is the index set of the configurations. Then, $\Omega = \{C_k : k \in K\}$ is the (finite) set of configurations. Given the sensed data of a worker as (2), a trained algorithm recognizes the configuration at time t with a probabilistic description (e.g.,[9]). Therefore, the recognized configuration at time t is a random variable, denoted by $\mathbf{c}_t$ and described by its probability distribution on Ω.

$$f(C_k) := Pr\{\mathbf{c}_t = C_k\} \quad \forall k \in K, \text{ and } \sum_{k \in K} f(C_k) = 1. \tag{3}$$

3.3 Motion

A motion of a worker is defined as a location change of the worker, a displacement or rotation of a configuration, or a change of configuration, over time. Therefore, sensed temporal-spatial data of a worker are used to analyze motions of the worker. Let $\{t_i : i = 1, 2, \dots\}$ be the series of sensor sampling times, indexed by i. l_i represents the location of a body point at time t_i. Then, the time series of the location is

$$l = \{l_i : i = 0, 1, \dots\}, \tag{4}$$

which traces a trajectory in the location measurement space. The time series of configurations can be represented by the time series of the spatial data in (2):

$$L = \{L_i : i = 0, 1, \dots\}, \tag{5}$$

and by the time series of the probabilistic recognition defined in (3) if applicable:

$$Pr(\mathbf{c}) = \{Pr(\mathbf{c}_i) : i = 0, 1, \dots\}. \tag{6}$$

$Pr(\mathbf{c})$ traces a trajectory in the probability measurement space for the configurations, which is in N_K dimensions. Specifically, the trajectory is on the space defined by $\sum_{k \in K} f(C_k) = 1$.

A motion, m_i, is detected at time t_i if the prior state (either a location or a configuration), $u_{i'}$, is switched to the current state, u_i, at t_i:

$$m_i := w(u_{i'} \to u_i); \tag{7}$$

wherein $u_i \neq u_{i'} \approx u_{i''}$, for any sampling time $t_{i''}$ between $t_{i'}$ and t_i (i.e., $i' < i'' < i$). The switch function in (7) can be defined using a metric for measuring configuration changes.

3.4 Action

An action is one or a sequence of meaningful configurations (or motions) that are driven by a goal (e.g., to complete a step of an assembly task) and produces an outcome (measured by some performance metrics). Consider an assembly task that involves N_S steps, indexed by s. The index set of steps is $S = \{1, 2, \dots, N_S\}$. An action driven by the goal of completing any step s of the task can be captured by the spatial-temporal data of the worker configurations in performing step s,

$$a_s = \{L_i : i \in I_s, s \in S\}, \tag{8}$$

where I_s is the time period for performing step s. The action can also be captured by the sequential motions involved:

$$a_s = \{m_i : i \in I_s, s \in S\}. \tag{9}$$

4. An Illustrative Example

4.1 The Experiment Setup

To implement our proposed models, a practical working scenario is simulated, as Figure 1 illustrates. A simplified operation i.e., inserting a nail into a workpiece using a hammer is chosen for the demonstration. The operation consists of a sequence of steps listed in Table 1. A Microsoft Kinect is used to capture the worker's actions in the operation. Figure 1(a) shows that the worker is in a sitting posture when performing the task and his legs are occluded by the workbench in front of him. Therefore, only the upper part of his body is considered in this study. Figure 1(b) shows the 17 joints for specifying configurations of the upper part of worker's body. The temporal-spatial data of these joints and the RGB images are recorded simultaneously for monitoring the worker's actions.

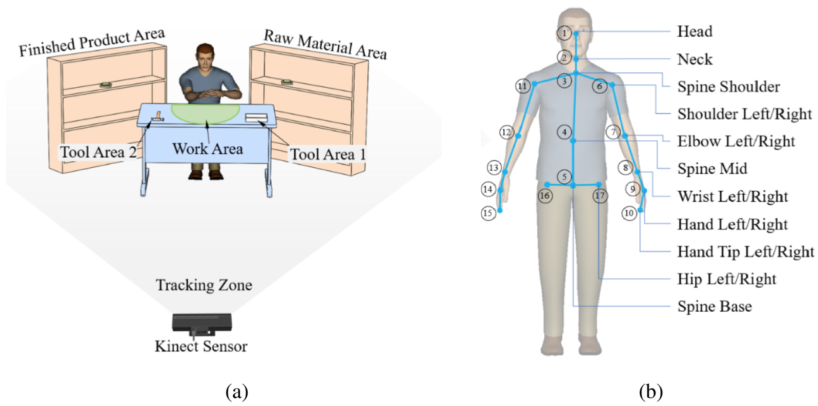

Figure 1: An illustrative example: (a) experiment setup; (b) the skeleton joints tracked

Table 1: Instructions of the task

Step	Instruction
1	Take the workpiece from the raw material area with the left hand
2	Put the workpiece on the workbench
3	Grab a nail from toolbox 1 using the left hand
4	Grab the hammer from toolbox 2 using the right hand
5(a&b)	Continue back and forth motion of the hammer
6	Return the hammer to toolbox 2 with the right hand
7	Take the part and put it on the finished product area using the right hand

4.2 An Experiment

Figure 2 illustrates the worker's typical configurations in the seven steps of the hammering operation, the corresponding RGB images, and the timestamps taken from a practical experiment. For example, the worker's action of reaching and grabbing the workpiece (i.e., step 1) took 0.300 seconds in this experiment. The action of performing this step, a_1, is a sequence of left hand motions, identified from a sequence of configurations of the left arm. Configurations of the arm are identified with five joints (6, 7, 8, 9, and 10). For instance, if we consider the 5th joint as the origin of the location measurement space, the spatial data (in meter) of the left arm configuration at $t = 0.300$ seconds are the following:

$$L_{0.300} = \begin{bmatrix} l_{6,0.300} \\ l_{7,0.300} \\ l_{8,0.300} \\ l_{9,0.300} \\ l_{10,0.300} \end{bmatrix} = \begin{bmatrix} -0.53786,\ 2.94239,\ 0.10453 \\ -0.68080,\ 2.97789,\ 0.04105 \\ -0.81667,\ 2.97218,\ -0.00607 \\ -0.86657,\ 2.98566,\ 0.00015 \\ -0.94280,\ 2.99148,\ -0.01636 \end{bmatrix}. \tag{10}$$

The analysis of the time series of the left arm configurations reveals that the worker took the workpiece at $t = 0.300$ seconds, positioned the workpiece on the workbench at $t = 1.315$ seconds, and grabbed the nail from the toolbox 1 at $t = 2.808$ seconds. Steps four to seven involve motions of the right arm. The right arm configurations are identified with another five joints (11, 12, 13, 14, and 15). The analysis of the time series of the right arm configurations describes that the worker grabbed the hammer from the toolbox 2 at $t = 4.463$ seconds, moved the hammer back and forth to punch the nail down until $t = 11.096$ seconds, returned the hammer back to the toolbox at $t = 12.369$ seconds, and

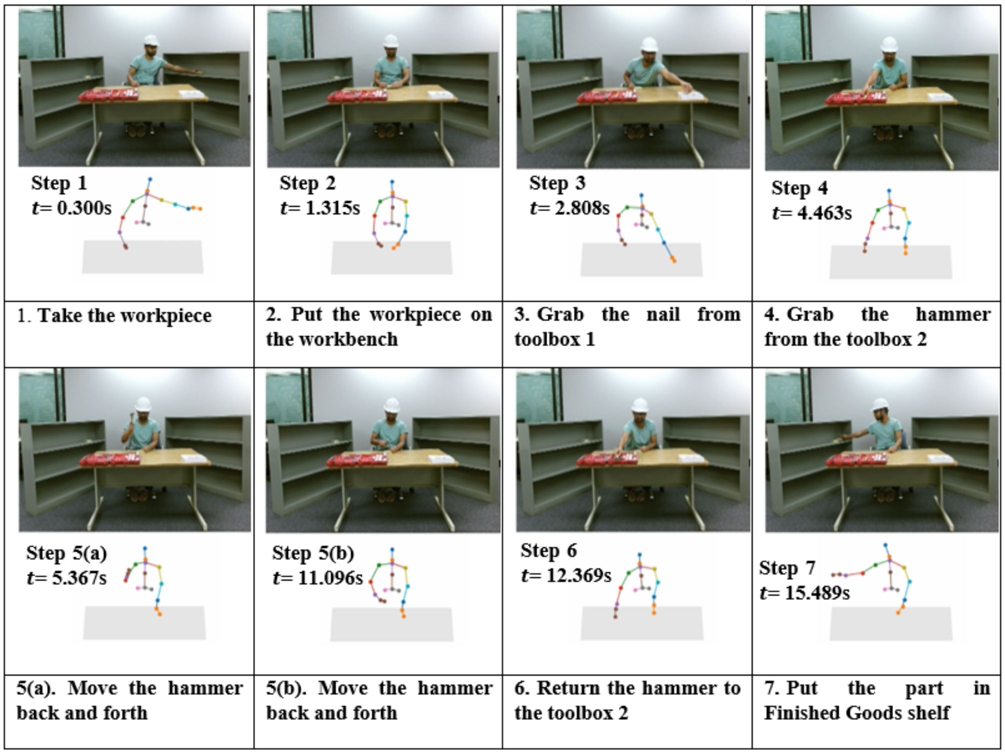

Figure 2: Steps of hammering operation performed by a worker

sent the finished part to the goods shelf on the right hand side at $t = 15.489$ seconds. Table 2 further summarizes the time that the worker spent for each of the seven steps of the operation in this experiment.

Table 2: Times of actions

Step	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Time Spent[second]	0.300	1.015	1.493	1.655	6.633	1.273	3.120

4.3 Repeated Experiments

We can let the worker repeat the experiment in Section 4.2 for multiple times. We can also let a group of workers perform this operation. The obtained temporal-spatial data of workers allow for studying the learning behavior and operational performance of workers.

- *Learning curves of a single worker's actions*: We let an unskilled worker to repeat the experiment so that we can study the learning curve of the worker's each action. For example, we statistically test if a decreasing trend of action time is observed on each of the seven actions over the repeated experiments.
- *Learning curves of a group workers' actions*: We let multiple unskilled workers to perform the experiment so that we can study the heterogeneity in workers' learning capability.
- *Statistical performance of a group*: Performance variation is anticipated even among skilled workers. We let a group skilled workers to perform the experiment to study the variation of their performances on each indivdiual step of the hammering operation, as well as the correlation among different steps.

5. Conclusions

The paper summarized the sensing technologies that are being used extensively in the smart manufacturing environment for collecting data on worker activities and worker-machine interaction. Mathematical models have been formulated with the capability of describing characteristics of worker activities like location, configuration, motion, and action. A case study pertaining to real life manufacturing operations has been delineated. The case demonstrated the use of processed sensor data and the developed math models for measuring worker performance at detailed levels (e.g., action). The paper also showed how accumulated performance data obtained from repeated experiments performed by either a single or multiple workers can be exerted to study various aspects of manufacturing workers. These include the learning behavior, within-group performance variation, and performance correlation between different steps of operations, all at the level of worker actions. The study of this paper demonstrates an opportunity for smart precise training and assistance of manufacturing workers. That is, we are able to identify any unskilled worker and the specific portion of each operation that the worker needs training or assistance. This allows us to train or assit workers only when needed.

Following the study of this paper, we will build decision models and solution algorithms to provide recommendations on optimal training and assistance of manufacturing workers. Then, we will integrate the training and assistance subsystem with the data analytics and modeling subsystem presented in this paper. We also have planned on implementing the proposed approach and models in a wide range of representative, complex manufacturing operations. These will allow us to assess the data analytics and modeling capabilities of the cyber-physical system we are developing for workforce management.

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