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Human Pose-based Labor Productivity Measurement Model

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Abstract: Traditionally, the construction industry has shown low labor productivity and productivity growth. To improve labor productivity, it must first be accurately measured. The existing method uses work-sampling techniques through observation of workers' activities at certain time intervals on site. However, a disadvantage of this method is that the results may differ depending on the observer's judgment and may be inaccurate in the case of a large number of missed scenarios. Therefore, this study proposes a model to automate labor productivity measurement by monitoring workers' actions using a deep learning-based pose estimation method. The results are expected to contribute to productivity improvement on construction sites.

Key words: deep learning, human pose estimation, labor productivity

1. INTRODUCTION

Globally, labor productivity in the construction industry is increasing at a slower rate than in other industries. Over the past 20 years, the global economic growth rate has increased annually by 2.8% and the manufacturing industry has increased annually by 3.6%. However, labor productivity in the construction industry has only increased by 1% [1]. Moreover, the construction industry in Korea has traditionally shown low productivity and low productivity growth. According to the Bank of Korea, the construction industry shows about 50% labor productivity compared to the manufacturing industry. This is well below average, even though the manufacturing industry has the best labor productivity [2,3]. In terms of construction work, only approximately 60% of working hours is considered productive work, and 30% of time is spent on standby, movement, suspension of work, and other non-productive activities [4].

To improve labor productivity, it must first be accurately measured. One of the existing construction labor productivity measurement methods is the work sampling technique, which uses the labor utilization factor. This technique is a method in which observers monitor workers' activities on site at certain time intervals and classify labor productivity into three categories: productive work, semi-productive work, and non-productive work. A disadvantage of the existing method is that due to the subjective nature of the observer dependent assessment, results can be variable. Another downside is that several instances are omitted because of the long time interval between sample measurements [5-9].

Meanwhile, computer vision is actively applied in various fields such as manufacturing, medical care, robotics, and the automobile industry. It is a technology that automatically extracts useful information from an image and analyzes data more efficiently than humans. In the construction industry, many studies on monitoring safety, productivity, and quality of construction sites using computer technology exist. In particular, most studies on monitoring productivity have focused on equipment [10-13], and few have been conducted to monitor workers' productivity using action recognition [14].

Unlike manufacturing sites, construction sites do not have a fixed space, but create new spaces. The creation of such a space is characterized by continuous changes in the surrounding environment. However, image recognition extracts the characteristics of workers despite the frequently changing background. It requires significant learning and extensive computation in the recognition process, thereby limiting its suitability for a construction site. A robust method is necessary that is less affected by the changing background and can recognize the unique characteristics of a worker.

This study proposes a human pose-based automated productivity measurement model to estimate robust action recognition for varying backgrounds. First, previous studies related to activity recognition are reviewed. Next, a human pose-based labor productivity measurement model is proposed. The model consists of a human pose and a productivity measurement part. The focus of this study was masonry work, which is essential for construction of apartment buildings, and has easily distinguishable poses. After training the proposed model, labor productivity was measured by applying the proposed model and the existing work sampling method, and the results were compared and analyzed. Finally, the significance and limitations of the proposed model are discussed.

2. LITERATURE REVIEW

2.1 Human pose model

In this study, the pose estimation model Google Teachable Machine, a web-based learning tool, was used for human pose estimation. The model consisted of PoseNet and MobileNet (Figure 1). First, when the RGB image is input, GoogleNet-based PoseNet estimates the x and y coordinate values of 17 keypoints of the person in the image. MobileNet classifies the pose category by receiving these keypoint values as inputs.

The training and inference processes of the Google teachable machine are as follows. First, we created class categories. After inputting the training dataset corresponding to each category, the model was trained. When the test dataset enters the learned model, it returns the results of the classification. A model trained in this manner has a light structure and can be executed on various computers or mobile devices.

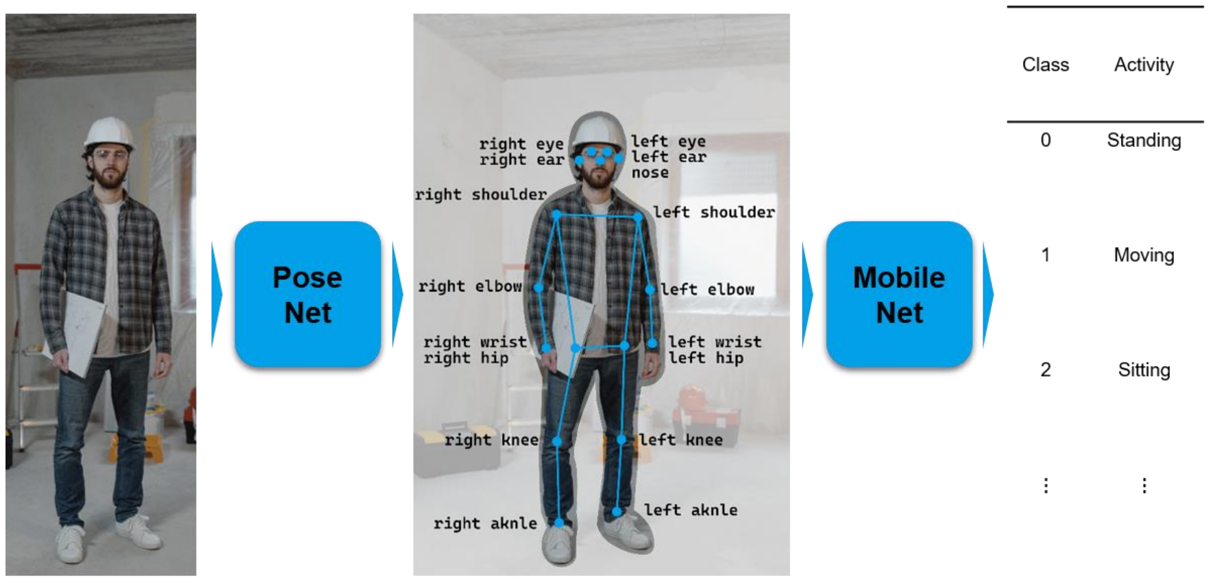

Figure 1. Human pose estimation model

2.2. Relevant studies

Computer vision is a field that enables human visual recognition ability using a computer, such as identifying people or objects and estimating poses in image data. In particular, the human pose estimation task is a technique for recognizing human poses by training and classifying a model by analyzing patterns, such as the outline of a body. There are two main pose estimation methods. The first is a technique that directly classifies an image and analyzes a pose in the background, and the other is to create a skeleton structure by extracting keypoints from the image and analyzing the pose by examining the structure. The skeleton structure technique can easily analyze poses in varying backgrounds. It separates the pose from the background, structures it and uses it as input to analyze the pose.

Computer vision technology is an active field of research in the construction industry. In particular, the majority of existing productivity monitoring studies focus on productivity measurement through motion estimation of construction equipment. Vahdatikhaki et al. (2015) proposed a robust optimization-based method that uses the geometric and operational characteristics of an excavator to improve the quality of pose estimation [10]. Soltani et al. (2017) proposed a model that determines the 2D skeleton of excavators based on videos received from on-site cameras [11]. Kim et al. (2018) developed an activity identification framework that incorporates the interactive aspects of earthmoving equipment operation [12]. Luo et al. (2020)

proposed a methodology framework for automatically estimating the poses of different construction equipment in videos [13].

In terms of labor productivity monitoring, Luo et al. (2018) proposed a two-stream CNN model that recognizes workers' activities by receiving and classifying video images into productive work, semi-productive work, and non-productive work [14]. However, their model uses RGB images and optical flow. Consequently the results are affected by cropped image size and worker location in the image.

Thus, this study proposes a labor productivity measurement model with robust performance for varying backgrounds using the human pose estimation method.

3. HUMAN POSE BASED LABOR PRODUCTIVITY MEASUREMENT MODEL

3.1. Construction activity category

A productivity measurement model was proposed for masonry work. Three categories were considered: productive work, semi-productive work, and non-productive work. Productive work included brick masonry and mortar filling, semi-productive work included mortar mixing and brick pitching, and other activities were classified as non-productive work (Table 1).

Table 1. Human pose classes for masonry work

Class	**Worker activity**
Productive	Brick masonry, mortar filling
Semi-productive	Mortar mixing, brick pitching
Non-productive	Rest, etc.

3.2. Model architecture

This section explains the method for measuring labor productivity using video images as input and post-processing of the values from the human pose estimation model. The model consists of two parts: worker pose estimation and productivity measurement.

First, worker pose estimation, a video image of time t is passed through the pose measurement model at one frame per f_1 second. A weight of 1 is assigned to productive work (p), semi-productive work (s), and non-productive work (n) as the initial value of the pose measurement model corresponding to the frame. If the remainder is 0, the work with the largest value (productive, semi-productive, non-productive) is regarded as an activity for $1/f_2 t$ of the total work by dividing the number of repeated frames by f_2/f_1. Labor productivity is the final value equal to the sum of the values obtained by multiplying productive and semi-productive work by $1/4$ among all works. (Figure 2).

Second, for labor productivity measurement, labor productivity is based on the pose estimation result from the previous pose estimation model. Labor productivity (LF= labor utilization factor) is measured using Equation (1) as follows [15].

$$LF = \frac{\text{number of productive workers} + (\text{number of auxiliary workers} \times \frac{1}{4})}{\text{Total number of workers}} \tag{1}$$

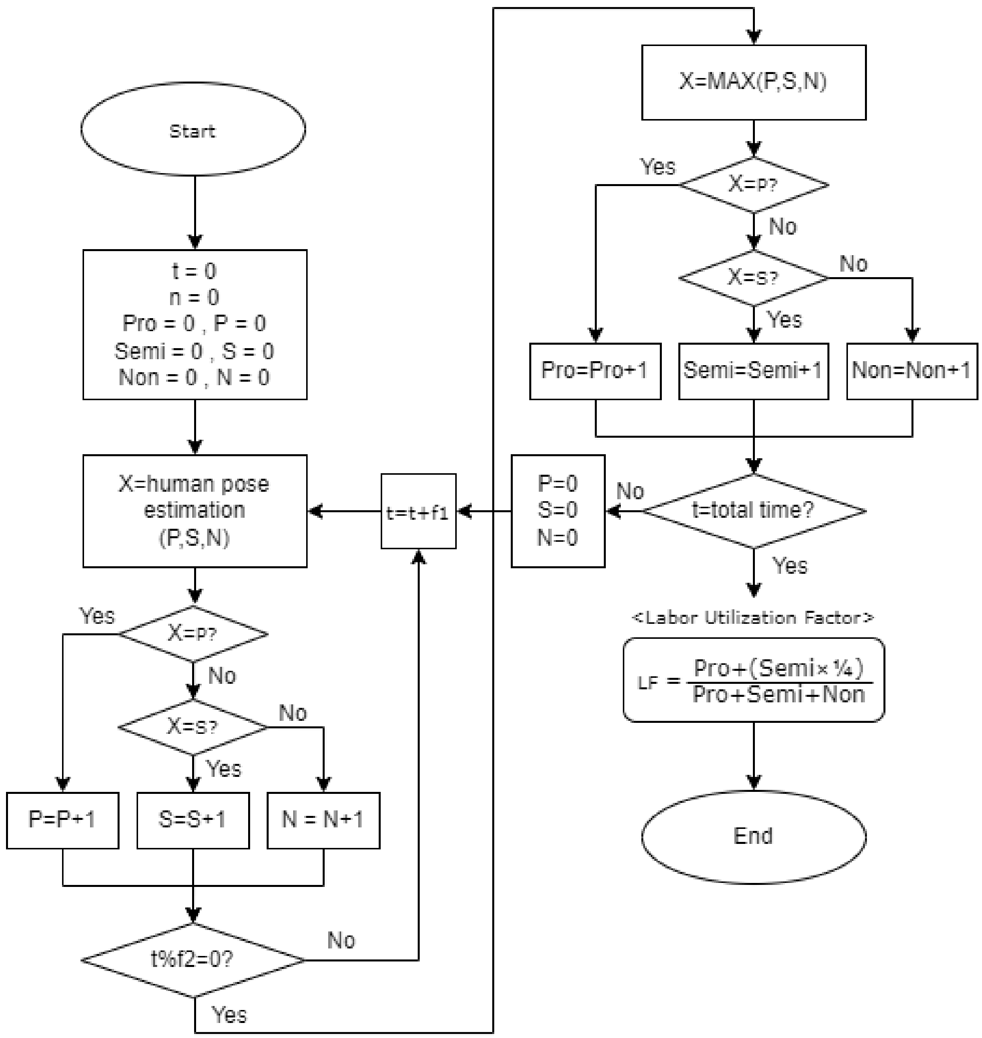

Figure 2. Algorithm of labor productive measurement model

4. CASE STUDY

The proposed model was verified by comparing a case study with the existing work sampling method. First, the proposed model was trained using the test dataset. Then, two methods were applied to the test dataset to compare the accuracy of labor productivity measurement.

The dataset was collected using on-site imaging and web scrapping techniques. Model training was conducted with 1561 training datasets, with 960 productive, 308 semi-productive, and 293 non-productive work data. The test dataset extracted 815 images at five-second intervals from two hours of crude construction image data, followed by the work productivity measurement. (Figures 3, 4)

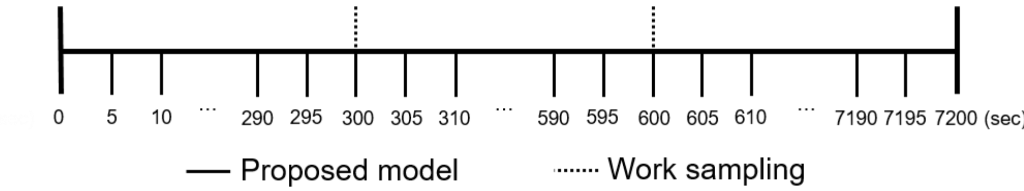

Figure 3. Sampling intervals

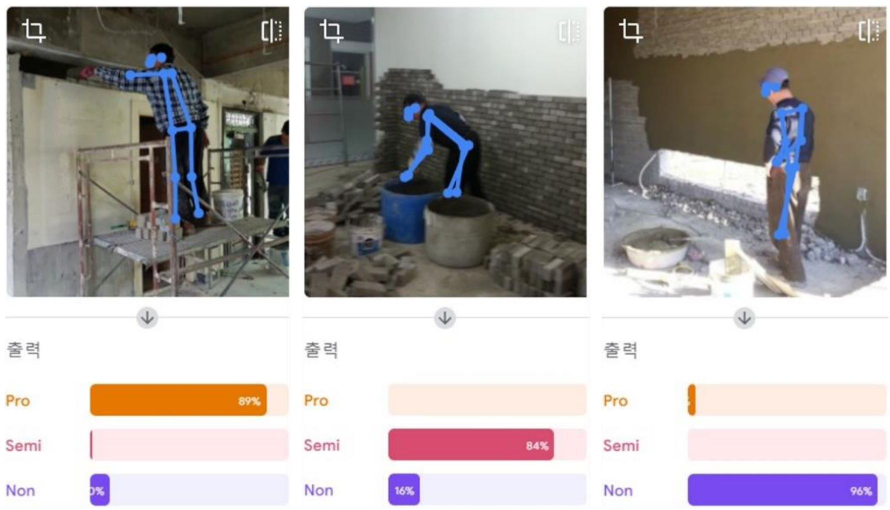

Figure 4. Samples of pose estimation results

Subsequent labor productivity was 87% with 690 productive, 76 semi-productive, and 49 non-productive tasks. The existing work sampling method measured the same images 18 times at five-minute intervals, capturing 14 productive tasks, four semi-productive tasks, and zero non-productive tasks. Labor productivity was 83.3%. The error between the two methods was 3.7% (Table 2).

Table 2. Proposed model validation

Division	Proposed model	Existing method	Difference
Productive	690	14	-
Semi-productive	76	4	-
Non-productive	49	0	-
labor productivity	87.0%	83.3%	3.7%

5. CONCLUSIONS

The construction industry, entrapped by low growth, has stagnated over the past 20 years, with foreign construction industries such as India and China recently emerging as strong competitors. Consequently, it is necessary to increase labor productivity to increase growth and gain international competitiveness. Because the construction industry has a high labor force and labor input cost, improvements in labor productivity will lead to an increase in overall construction productivity. In other words, it can add greater value with the same resource inputs, withstand low growth and simultaneously remain competitive.

To improve labor productivity, it must first be accurately measured. However, the existing method requires additional personnel to measure labor productivity. Additionally, the results may differ depending on the observer and may be inaccurate owing to intermittent observations omitting parts of the working day.

Therefore, this study proposes an automated model for measuring labor productivity. The model analyzed the worker's actions effectively by extracting key points from the image. And The model was verified by comparing a case study with the existing work sampling method. Labor productivity was successfully measured, and the error between the two methods was 3.7%. The proposed model offers the advantage that personnel are not required to measure productivity. In addition, if only image data can be collected, productivity can be measured for all activities and workers. Therefore, labor productivity can be measured with improved reliability compared to the traditional work sampling method.

Further studies will be conducted to improve the accuracy of the model by training additional datasets. Also, further studies will use a multiple pose estimation model to measure multiple workers simultaneously.

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