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Research paper

Agricultural worker behavioral recognition system for intelligent worker assistance☆

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ABSTRACT

In the present study, we developed a worker behavioral recognition system for a single targeted worker to understand his three specific types of worker behavior for producing peas, namely, watering, seeding, and harvesting, performed along a furrow. The three behavior types were further classified into 14 behavior subtypes and six behavior categories. The 14 behavior subtypes were modeled by 14 hidden Markov models (HMMs): 10 for harvesting behavior, 2 for seeding behavior, and 2 for watering behavior. In the experiments, the targeted worker twice performed the three types of behaviors facing the left ridge and the right ridge along a single specific furrow within a range of 5–25 m from a pan-tilt-zoom camera. The watering and seeding behaviors were performed in the same field condition as the actual field. The harvesting behaviors were faithfully reproduced by the worker with his huge experience in the non-crop field. The recognition rates for watering and seeding were approximately 98% for the watering-left category, 97% for the watering-right category, 100% for the seeding-left category, and 94% for the seeding-right category. For harvesting, the recognition rates for five HMMs in the harvesting-left category ranged from 26% to 100%, and the overall recognition rates for five HMMs in the harvesting-right category ranged from 44% to 100%. Although the recognition rates of two HMMs were too low in harvesting categories, the behavioral recognition system achieved the robust responses to the harvesting behaviors by applying OR operation to the outputs of the HMMs.

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1. Introduction

The Japanese agricultural sector faces a number of serious problems, such as depopulation, a rapidly aging workforce, the extreme physical workload required, and hazardous working conditions. Consequently, the number of Japanese agricultural workers in 2011 was approximately 1.8 million, which represents a decline of approximately 540,000 from 10 years ago. Furthermore, the percentage of agricultural workers over 65 years of age is currently approximately 60%. Japan's unemployment rate in 2011 was approximately 4.5%, and the percentage of non-regular staff members has been increasing since the 1980s. As a result, the increasing unemployment and non-regular employment rates among young people are becoming one of the nation's more serious problems. Accordingly, the problems facing the agricultural sector must be solved while taking into account the workforce imbalance between large cities and rural areas, the generation gap, and the large number of unskilled workers.

The field of automation technology has benefited from rapid developments over the past ten years. These developments include autonomous tractors and combine harvester navigation systems equipped with global positioning system (GPS) devices, along with product harvesting and quality grading systems with machine vision. However, while such products and systems reduce the human workload and save time, their utility and applicability is restricted to their designed fields, and they have no interactive functions that allow collaboration with human workers in other fields. Moreover, such systems do not provide opportunities for unskilled workers to work in the agricultural sector or to receive education and training related to agricultural work.

In our study, we propose an intelligent agricultural worker assistance system designed to enable unskilled and semiskilled operators at remote sites to control agricultural vehicles and robots

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via the Internet. The worker assistance system autonomously controls cameras that track workers and identifies workflows based on worker behaviors. To assist workers, the system also formulates assistance request menus, such as the timings, locations, and tasks that need to be performed, and sends the requests to operators at remote sites. Operators at remote sites then control vehicles and robots to provide the requested assistance to field workers. The worker tracking system and the worker behavioral recognition system are essential in developing the worker assistance system.

In our study, to specifically design an intelligent agricultural worker assistance service for farmers, we focused on specific farm operations performed by a farmer in Hidaka District, Wakayama Prefecture, Japan. The farmer was a large-scale family farmer with an annual income of over 20 million yen. This farmer annually produced various kinds of crops such as 10 ares of green peas, 30 ares of snow peas, 20 ares of kidney beans, 1.1 ha of rice, 5 ares of sweet peas, 50 ares of watermelons, and 1 ha of ume (Japanese plum) in a hilly and mountainous area. Because the district is Japan's top producer of green peas, snow peas, and umes, many farmers in the district improve the performance of farm operations by taking advantage of human resources such as their children and part-time workers. Especially, the children of large-scale family farmers in the district tend to understand the workflow from the behavior of their parents and autonomously provide intelligent assistance without request from the parents. The assistance provided by the children enables farmers to improve the efficiency of farm operations as well as to reduce the workload. However, the children cannot always help their parents because they have to go to school, sometimes go out, and may move to urban area after leaving school.

Our first goal is to develop an intelligent worker assistance system with a performance equivalent to that of a child in the district. To design the first prototype, we focused on farm activities such as walking, watering, seeding, and harvesting in a field of green peas and snow peas. These activities are performed by farmers facing the left or right ridge and going-and-returning along each furrow in the field. Watering and seeding are performed by workers on the same day, and seeding is performed just after watering. Because the activities of watering, seeding, and harvesting are performed manually by workers, a large amount of human resources is required during a short period.

The children sometimes stand at the end of a furrow to observe the workflow and determine their next actions. In the present study, a worker tracking system placed at the end of a furrow monitors the behavior of a single worker in the furrow. If the system, like the children in the district, can recognize the farmer's behavior, it can predict the tasks to be performed before or after the tasks are performed by the farmers, such as seeding after watering, covering seeds with a layer of soil after the completion of seeding, transporting plant nettings and steel poles for managing crops after seeding, and driving a vehicle for transporting harvested products. Behavioral recognition enables our system to understand the workflow and determine the request menus, such as the timings, locations, and tasks that need to be performed for providing intelligent support.

In a previous study, to track a moving worker in a furrow, we developed a real-time single-agricultural-worker tracking system with image processing (Morio et al., 2012). The tracking system consists of a single pan-tilt-zoom (PTZ) camera, a worker uniform with attached red-blue color markers, and two types of particle filters to track the markers on the uniform. In operation, the tracking system is capable of detecting the position of the uniformed worker, along with his or her standing and sitting postures, within a sensing range of approximately 38 m (resolution: approximately 1 m). This range is sufficient for detecting a worker at a monitored furrow in a cultivated field. This system is also capable of detecting eight separate posture types for the color markers to express the worker's stances.

As another new function of the worker tracking system, we developed an agricultural working motion detection system using the eight posture types of the color markers on the worker uniform for recognizing worker behavior (Morio et al., 2014). The working motion detection system used the color marker posture sequences to detect 12 types of working motions, such as turning counterclockwise or clockwise, squatting, and moving arms left or right while standing or sitting, as performed by a worker along a furrow in the agricultural field. The motion detection system could robustly and separately respond to the targeted motions when the positions and posture patterns of the color markers on the worker uniform changed depending on the worker's behavior. However, when the positions and posture patterns of the color markers were not changed, the system could not acquire any information about the worker behavior. Therefore, a motion detection system is not used in the present study.

To robustly acquire information about working behavior even if the positions and posture patterns of the color markers were not changed, we developed an agricultural worker posture recognition system (Tanaka et al., 2014). The worker posture recognition system used a worker's silhouette shapes and eight types of posture patterns of the color marker on a worker uniform to recognize worker postures. The posture recognition system is capable of identifying 18 groups and eight categories of worker postures performed by a single worker walking, turning, bending, squatting, stooping, and moving his arms along a furrow in the agricultural field. The system achieved a recognition rate of approximately 90% on more than 15,000 test samples performed by two workers.

In the present study, using worker posture sequences acquired by the worker posture recognition system, we develop a worker behavioral recognition system to recognize three specific types of worker behavior for producing green peas and snow peas – watering, seeding, and harvesting – performed by the single targeted farmer along a furrow in a field. This worker behavioral recognition system is the first prototype built using the worker tracking system and the posture recognition system developed in previous studies. In particular, as a first step towards developing an intelligent worker assistance system, the prototype is optimized by allowing it to be used by the targeted farmer. As many different varieties of behavior patterns are performed by only the single targeted farmer, the worker posture recognition system and the worker behavioral recognition system is optimized only for the single targeted farmer in this study.

In the present paper, we describe 18 types of postures detected by the developed posture recognition system and 14 hidden Markov models (HMMs) to recognize the three different types of harvesting behavior. HMMs are stochastic signal models that have been used successfully in speech recognition and in handwriting recognition. Rabiner (1989) applied HMMs for speech recognition, and Starner and Pentland (1995, 1998) developed a hand gesture visual recognition system for American Sign Language (ASL) by using HMMs. The sequences of specific features of hand motions such as the x and y positions of each hand, the angle of the axis of least inertia, and the eccentricity of the bounding ellipse of each hand in an image were extracted by using color gloves and modeled by HMMs. Zafrulla et al. (2011) developed an ASL recognition system with HMMs by using the depth information acquired by a Microsoft Kinect sensor with a detection distance from the sensor of less than 5 m. In our previous studies, HMMs to recognize container-lifting behavior were designed for determining the timing to assist product-shipping operations in indoor workplaces (Morio et al., 2013). This system was found to be effective within a

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