Lower body action classification using unlabeled predicted motion

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***Abstract*—In this study, a rule-based motion classification method was presented for the lower extremity motions prediction and classification for exoskeleton robot lower extremity support. With the CMU public DB and additional motion DB using Xsens device, the joint angles of the lower extremity for the next second was predicted using the bidirectional LSTM algorithm. By defining the motion vector of the predicted lower extremity joint angle and calculating the motion score, future lower extremity motions could be classified as walking, squat, and stoop without labeling process. The proposed algorithm is fast in calculation and does not require label work, so it can be easily loaded into low-cost devices, so it is expected that it can be applied not only to exoskeleton robot control but also to wearable smart devices**

Keywords— exoskeleton robot, motion prediction, motion classification

I. INTRODUCTION

Recently, interest in wearable devices is increasing to support and protect the elderly and workers [1]. Support for the movement of the lower body occupies a large portion, and in order to provide appropriate external force support without interfering with human movement, control based on analysis of the current human motion and prediction and classification of future movements is required [2]. Data labels are not required in the process of predicting motion, but there is a problem in that motion classification requires time-consuming and costly labeling. In this study, we would like to present a method for classifying motions without data labels based on the prediction results of lower body motions

II. HUMAN MOTION DATABASE

A. CMU Human Motion Database

Various databases for researching human body motion are emerging, and representative examples include CMU(Carnegie Mellon University) DB [3] as shown in Fig.1, and Human 3.6M [4]. Human 3.6M has disadvantages such as license conditions. In this study, CMU DB, which is a fully open DB, was used as shown in Fig.1. CMU DB provides whole-body movement data for a total of 144 subjects, including walking, dancing, various sports, daily movements and special movements. Among the CMU DB, 146 walking clips of various styles, and 18 motion clips including floor and chair sitting motions including squat and stoop were selected. Since the CMU DB is not a DB with clearly refined motions for lower body motions, the walking motion class includes some motions such as standing and squatting, and sitting motions are included in walking.

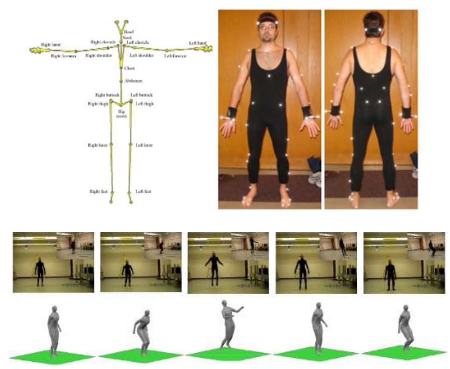

Fig. 1. CMU human motion capture dataset

B. Additional data using Xsens instruments

Xsens MVN system [5] was used for additional motion data acquisition. The equipment is a system that estimates the user's posture using inertial sensors attached to each part of the body, and provides acceleration and gyro sensor data and joint angles. As shown in Fig. 2 while wearing the Xsens MVN, one hour of motion DB for motions such as walk, squat and stoop were collected.

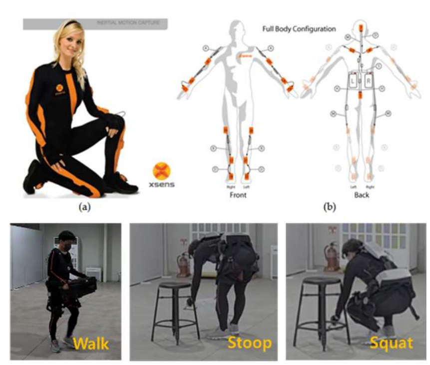

Fig. 2. Xsens MVN device-based motion data collection

III. Human Motion Classification

A. Lower Body Motions

The main targets of the exoskeleton lower extremity support are the hip joint and the knee joint, and as a single joint, they are the most active part in the human body. In the exoskeleton device for the lower limbs, the supporting motions include walking, squatting, and stoop, which occur mainly in general labor environments. Fig. 3 shows the analysis of changes in the 1-second section of the lower extremity joints for the walking, squat, and stoop motions selected from the CMU DB described above. The left side of Fig.3 is the change of the hip joint and knee in the walking motion, and there is a characteristic that the left and right joints are symmetrically repeated within a specific section. The selected CMU DB is characterized by a wide range of motion of the joints of the lower limbs as it includes motions in low postures such as monkey walking. The right side of Fig.3 is sitting motions related to squat and stoop, and the left and right joints tend to move in the same direction at the same time. In the CMU DB, walking is included in some sections of squat and stoop motion clips, and walking also includes motions such as walking in a low posture, so the motion areas tend to relatively overlap.

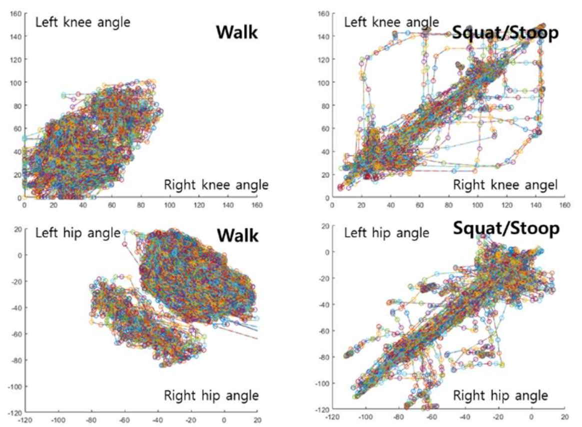

Fig. 3. CMU DB knee and hip motions for walk and squat/stoop

Fig.4 shows the motion results for motions such as walk, squat, and stoop collected by Xsens equipment. In the case of walking, the hip joint and knee clearly show the characteristic of repeating symmetrically in a specific area. In the case of squat and stoop, the characteristics of the left and right joints moving in the same direction at the same time are well revealed. On the other hand, in the case of a squat, the hip joint and knee move together, but in the case of a stoop, only the hip joint tends to move.

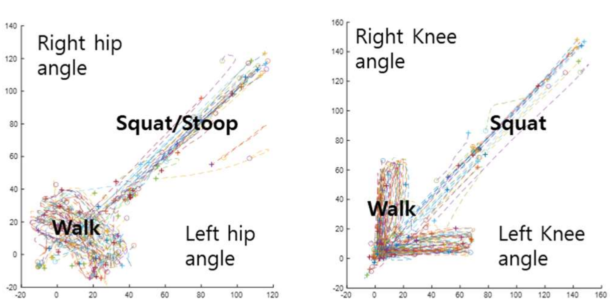

Fig. 4. Xsens DB knee and hip motions for walk and squat/stoop

B. Motion Prediction

In order to effectively support the exoskeleton robot, it is effective to predict the future movement of the wearer and provide appropriate external force. In this study, we developed an algorithm that predicts motion from the present to 1 second in the future for motion from the past 1 second to the present as shown in Fig.5[6]. As shown in Fig. 6, the developed algorithm is composed of a 3-layer bidirectional LSTM[7] and learned to output joint angles of 0 to 1 second in the future for inputs of past few seconds in the past. Fig. 7 and 8 shows the changes in the joint angles of the left and right hip and knee joints measured by motion capture equipment and predicted by the developed algorithm.

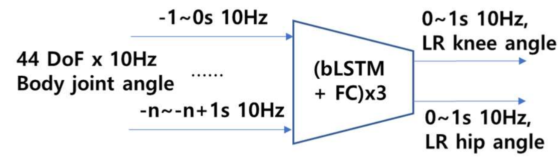

Fig. 5. Bidirectional LSTM based joint angle prediction structure

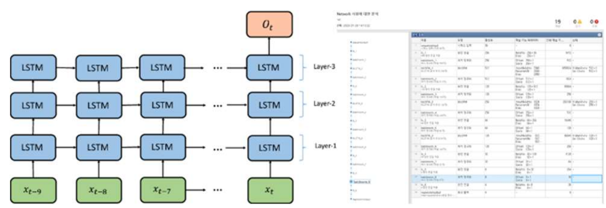

Fig. 6. Bidirectional LSTM based joint angle prediction structure

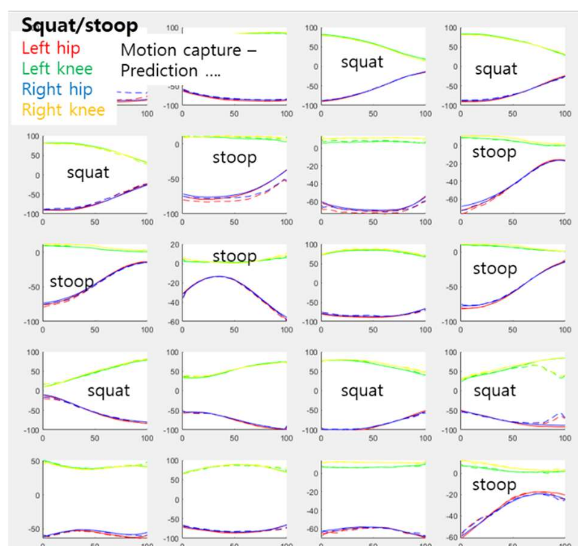

Fig. 7. Joint angle predictions in 0~1s during squat and stoop

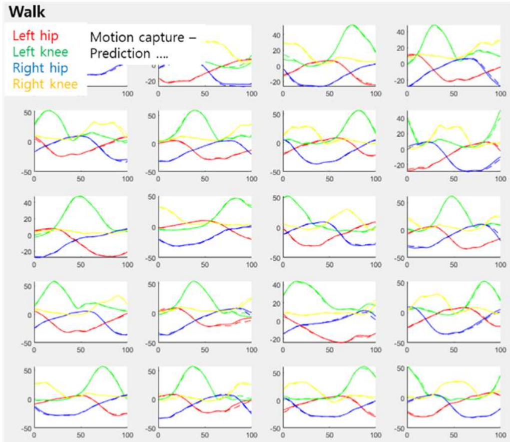

Fig. 8. Joint angle predictions in 0~1s during walk

C. Action Classfication

Various motion classification methods have been introduced [8, 9], but there is no clear boundary line for motion classification in real situations, and there is a characteristic that requires quick judgment in real time. To solve this problem, a rule-based motion classification method was developed. As illustrated in Fig. 9, the development method defines the left joint angle as x and the right joint angle as y for the hip and knee joints, and converts the change in joint angle up to 1 second into a motion vector. For the converted motion vectors, motion score = mean([x*y])/std([x*y]) is calculated where mean is the mean and std is the standard deviation. A motion score is calculated for each hip joint and knee joint to obtain two scores. Fig. 10 shows the motion scores for the hip and knee joints for the CMU DB. In the picture on the left, in the case of walking, both hip and knee joints show relatively low scores, and squat and stoop show relatively high scores. In the CMU DB, there are cases where motions such as walk, squat, and stoop are mixed, result shows overlapping area.

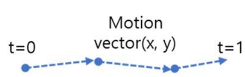

Fig. 9. Definition of joint angle motion vector

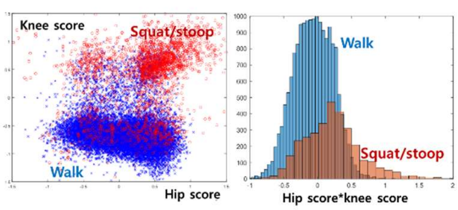

Fig. 10. Lower body joint angle motion score distribution for CMU DB

As shown in Figure 11, in the additional data using Xsens, it shows more clear patterns. In the case of walking, the movement of the left and right joints is in the opposite direction, and the magnitude of change is small, so both the hip and knee joints tend to have low motion scores. In the case of the squat, both the hip joint and the knee joint scored high, and in the case of the stoop, only the hip joint tended to have a high score.

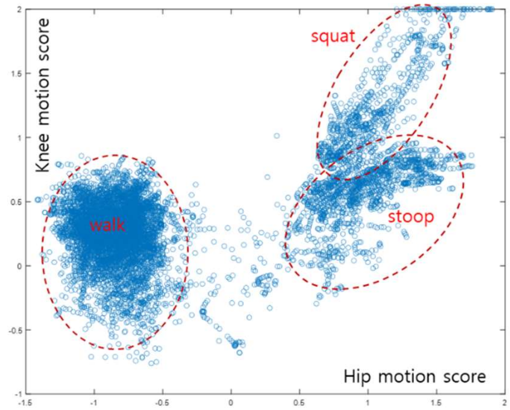

Fig. 11. Lower body joint angle motion score distribution for Xsens DB

IV. Conclusion

In this study, a rule-based motion classification method was presented for the lower extremity predicted motions for exoskeleton robot lower extremity support. The CMU public DB and additional motion data using Xsens device were used. The joint angles of the lower extremity for the next 1 second was predicted using the bidirectional LSTM algorithm, using past few second motion. By defining the motion vector of the predicted lower extremity joint angle and calculating the motion score, future lower extremity motions could be classified as walking, squat, and stoop without labeling process. The proposed algorithm is fast in calculation and does not require label work, so it can be easily loaded into low-cost devices, so it is expected that it can be applied not only to exoskeleton robot control but also to wearable smart devices.

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