Preliminary Design of an Environment Recognition System for Controlling Robotic Lower-Limb Prostheses and Exoskeletons

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***Abstract* - Drawing inspiration from autonomous vehicles, using future environment information could improve the control of wearable biomechatronic devices for assisting human locomotion. To the authors knowledge, this research represents the first documented investigation using machine vision and deep convolutional neural networks for environment recognition to support the predictive control of robotic lower-limb prostheses and exoskeletons. One participant was instrumented with a battery-powered, chest-mounted RGB camera system. Approximately 10 hours of video footage were experimentally collected while ambulating throughout unknown outdoor and indoor environments. The sampled images were preprocessed and individually labelled. A deep convolutional neural network was developed and trained to automatically recognize three walking environments: level-ground, incline staircases, and decline staircases. The environment recognition system achieved 94.85% overall image classification accuracy. Extending these preliminary findings, future research should incorporate other environment classes (e.g., incline ramps) and integrate the environment recognition system with electromechanical sensors and/or surface electromyography for automated locomotion mode recognition. The challenges associated with implementing deep learning on wearable biomechatronic devices are discussed.**

I. Introduction

Designing effective control systems represents a leading challenge for roboticists and engineers working on wearable biomechatronic devices for assisting human locomotion. Robotic lower-limb prostheses and exoskeletons can enable geriatrics and rehabilitation patients to perform dynamic movements (e.g., staircase ascent) comparable to able-bodied individuals, which necessitate significant amounts of positive mechanical work about the lower-limb joints [1]-[6]. Most robotic lower-limb prostheses and exoskeletons have included hierarchical control systems, featuring high, medium, and low-level controllers [1], [3], [5], [7]-[9]. The high-level controller recognizes the patient's locomotion mode (and intent) by analyzing data from wearable sensors, and subsequently selects the corresponding finite state machine. The medium-level controller converts the estimated locomotion mode into desired device mechanics like robotic joint kinematics or mechanical impedances. The low-level controller computes the error between the device's current and desired mechanics and drives the onboard actuators to minimize the error through feedforward and feedback controls [1], [3], [6]-[7].

Transitioning between different locomotion modes (e.g., level-ground walking to staircase ascent) remains a significant challenge. For instance, the Össur Power Knee (Iceland), the only commercially-available powered lower-limb prosthesis, and Indego lower-limb exoskeleton (Parker Hannifin, USA) both require compensatory movements to manually switch between different locomotion modes [4]. In recent literature, automated pattern recognition algorithms using experimental measurements from various sensors have demonstrated more accurate and quicker locomotion mode recognition, the most prevalent algorithm being linear discriminant analyses [10]-[17]. Other related investigations have used support vector machines [7], [9], [13], [17], Gaussian mixture models [8], and dynamic Bayesian networks [4], [18]-[20].

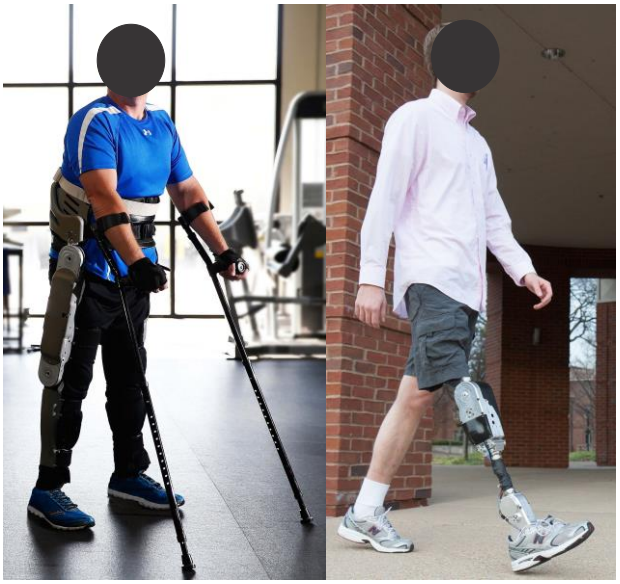

Fig. 1 Robotic lower-limb prosthesis and exoskeleton with onboard electromechanical sensors. Photographs courtesy of Dr. Michael Goldfarb (Vanderbilt University, USA).

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Different electromechanical sensors have been embedded into robotic lower-limb prostheses and exoskeletons and used for automated locomotion mode recognition, including rotary encoders [1], [3]-[6], [20], potentiometers [4], [8], strain gauge load cells [4], [8], [18]-[20], and inertial measurement units [3]-[6], [17], [19]-[20] (Fig. 1). Although electromechanical sensors allow for fully-integrated systems, these sensors merely respond to the patient's movements. In contrast, the electrical potentials of biological muscles, as experimentally recorded using surface electromyography (EMG), precede movement initiation and therefore could predict locomotion mode transitions [3], [11], [13]. Many recent investigations, especially those involving robotic lower-limb prostheses, have considered combining electromechanical sensors with surface EMG, aptly termed neuromuscular-mechanical data fusion [10], [12]-[16], [19]. Neuromuscular-mechanical data fusion for continuous locomotion mode recognition originated from Huang's group [13]. Combining electromechanical sensors with surface EMG has demonstrated improved locomotion mode recognition accuracies and computation times compared to implementing either system individually [10], [12], [19].

Despite the promising initial performances in automated locomotion mode recognition with neuromuscular-mechanical data fusion, further improvements are warranted since even occasional misclassifications can cause injuries, particularly when involving staircases [7], [12]-[13], [21]-[22]. Moreover, neuromuscular-mechanical data measurements are i) patient-dependent, therefore requiring time-consuming experiments to amass individual databases, ii) subject to intra-mode and inter-day differences, and iii) have limited prediction horizons [3], [7], [11], [21], [23]. Drawing inspiration from autonomous vehicles and robotics [24]-[25], augmenting neuromuscular-mechanical data with future environment information could improve the predictive control and obstacle avoidance of robotic lower-limb prostheses and exoskeletons (see Fig. 2) [1], [10], [15], [21], [26]. Such information would precede modulation of the patient's muscle activations and/or walking biomechanics, therein enabling more accurate and quicker locomotion mode recognition [12], [15], [22].

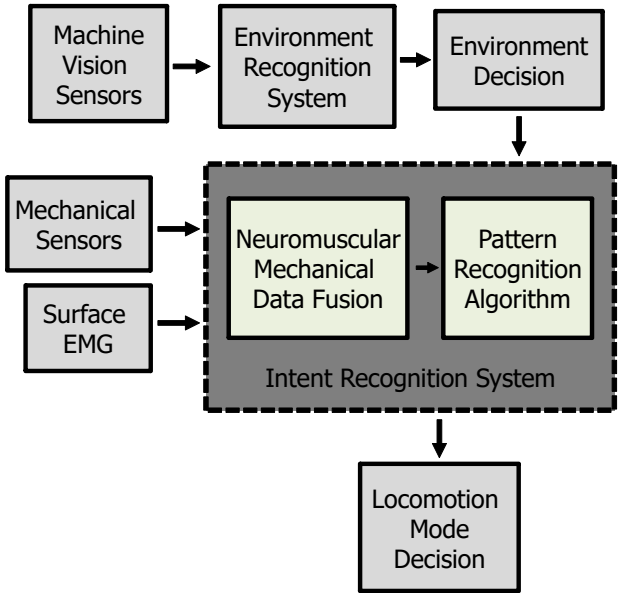

Fig. 2 Example of an automated locomotion mode recognition system (high-level controller) for robotic lower-limb prostheses and exoskeletons.

Preliminary research simulating oncoming environments via adaptive prior probabilities in linear discriminant analyses showed that including environment information improved the locomotion mode recognition accuracies when compared to excluding such information [10], [12]. Huang's research group originally developed a wearable environment recognition system, encompassing an inertial measurement unit and laser distance sensor, to approximate the geometry of the oncoming environment and provide supplementary information to the locomotion mode recognition system [14]-[16], [22]. Several researchers have recently explored vision-based systems for environment recognition to control biomechatronic devices, including Hargrove's group [17], [21], [23] and Varol's group [7], [9]. Compared to laser distance sensors, vision systems can provide information about the complete field-of-view and recognize physical obstacles and topography changes within peripheral locations [21]. The system from Hargrove's group included a wearable camera (Microsoft Kinect, USA) and used standard image preprocessing algorithms [21], [23]. Although their system performance was satisfactory, the computations were time-consuming (i.e., average 8 seconds/frame) and was evaluated using only five sampled images [21], [23].

The system from Varol encompassed a leg-mounted depth sensing camera (Softkinetic, Belgium) and used support vector machines for classifying different environments using hand-engineered features from depth-difference images [7], [9]. Their system achieved 94.1 % overall classification accuracy [7]. The authors acknowledged that deep learning algorithms like convolutional neural networks often outperform support vector machines for image classification [7] and therefore have become the standard in computer vision [27]. Moreover, depth cameras have limited capture volumes [28]. Building upon these previous investigations, the following research involved the preliminary design of an environment recognition system, using machine vision and deep convolutional neural networks, for augmenting the predictive control of robotic lower-limb prostheses and exoskeletons.

II. Methods

An environment recognition system was developed with the intention of supporting the automated locomotion mode recognition systems of lower-limb biomechatronic devices (see Fig. 2). Since accurate locomotion mode recognition and transitioning is especially important for staircase ambulation, this research focused on recognizing staircase environments. A deep convolutional neural network was trained to recognize three walking environments: level-ground, incline staircases, and decline staircases. Contrasting previous investigations that used hand-engineered features [7], [9], [21], [23], the current data-driven method automatically learned the optimal image features from the training dataset.

A. Experimental Data Collection

Comparable to previous research [26], one participant was instrumented with a battery-powered, chest-mounted RGB camera system (GoPro Hero4 Session); photograph shown in

Fig. 3. Chest-mounting provides less relative body movement than head or lower-limb mounting and, unlike limb-mounted systems [7], [9], [17], facilitates the wearing of pants without obstructing the field-of-view. Note that 3D information could have been attained using multiple synchronized RGB cameras [28]. Whereas previous studies of environment recognition systems have been limited to known laboratory environments [10], [14]-[15], [22], the current participant walked around the University of Waterloo campus [video link][1] while collecting RGB images of unknown outdoor and indoor environments with variable lighting, occlusions, signal noise, and intraclass variations. Data were collected at various times throughout the day, therein accounting for different lighting conditions. The sampled field-of-view was approximately 3 meters ahead of the participant. The images were collected at 60 frames/second with a 1280×720-pixel resolution and stored on a 64-GB microSD memory card. The wearable camera system weighs around 0.3 kg and includes a rechargeable lithium-ion battery. Approximately 10 hours of video footage (i.e., amounting to 2,055,240 sampled images) were collected during ten, 1-hour walking sessions. The RGB image dataset can be downloaded from IEEE DataPort [click link][2].

Since there were minimal differences between consecutive images at 60 frames/second, the dataset was downsampled to 1 frame/second for training the convolutional neural network. However, for real-time control and implementation on robotic lower-limb prostheses and exoskeletons, higher sampling rates would be more advantageous for effective locomotion mode transitioning. Similar to previous research [29], the images were cropped to 1:1 aspect ratios and resized to 224x224 pixel resolutions via bilinear interpolation. Overall, 34,254 sampled images were individually labelled and preprocessed, including 27,030 for level-ground, 3,943 for incline staircases, and 3,281 for decline staircases. There was subjectivity associated with manually labelling the environment classes, particularly near transitions. For transitioning from staircases to level-ground environments, the images were labelled as staircases whenever the staircase was visible inside the sampled field-of-view. For transitioning from level-ground to staircase environments, the images were labelled as staircases provided that the participant was within 1-2 steps and forward-facing the staircase. Images were labelled by one designated researcher for consistency.

Fig. 3 Photograph of the wearable camera system used for experimental data collection and environment recognition.

[1]https://www.youtube.com/watch?v=ulOLpRmw6so&feature=youtu.be

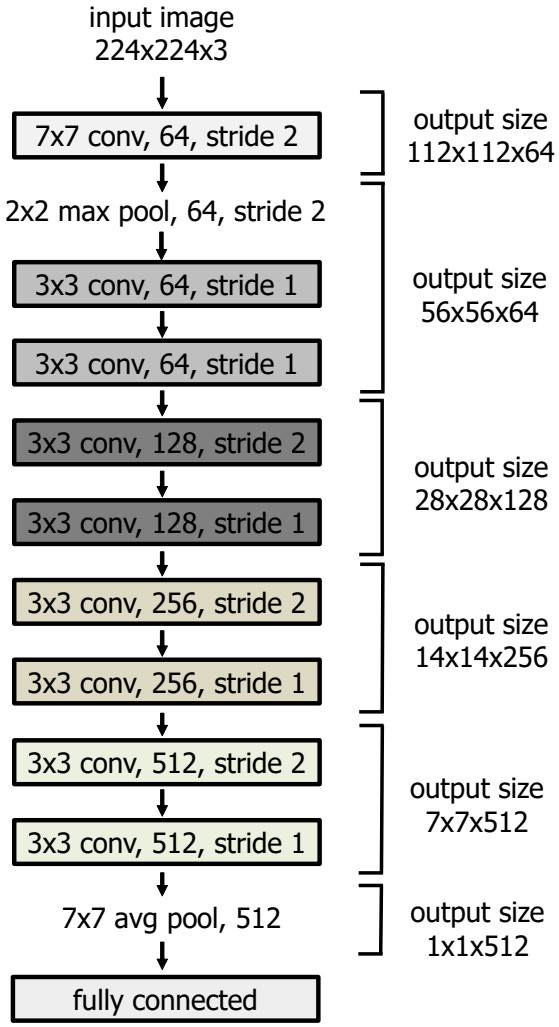

Fig. 4 Schematic of the deep convolutional neural network including convolutional layers, maximum and average pooling layers, and a fully connected layer.

B. Deep Convolutional Neural Network

The deep convolutional neural network was developed in TensorFlow 1.10 software (Google Brain, USA). Given that the classification problem was relatively small (i.e., involving three environment classes), a 10-layer convolutional neural network architecture was implemented (see Fig. 4). Shortcut connections and batch normalization were not incorporated since such design features are generally intended for extremely deep networks [29]. The convolutional neural network mainly used 3x3 filters. Besides the maximum and average pooling layers, downsampling was performed using convolutional layers with strides of two. Though absent from Fig. 4, rectified linear units (ReLu) followed each convolutional layer [27]. The neural network concluded with one fully-connected layer, wherein softmax regression computed the probabilities of the different walking environments (i.e., classes).

[2]https://ieee-dataport.org/documents/wearable-rgb-camera-images-human-locomotion-environments

Five-fold cross-validation was implemented, whereby the image dataset was separated into five individual folds (i.e., including two data-collection sessions apiece) and each fold was trialed for validation. Each data-collection session was therefore used for both training and validation. Since there were class imbalances among the dataset, the level-ground and staircase environments were undersampled and oversampled in accordance with the class priors of each fold during training, respectively, to obtain uniform distributions. The images were normalized by subtracting the average pixel intensities from each fold. Weights were initialized with Xavier initialization [30]. The neural network underwent 2000 training iterations using a batch size of 256 (i.e., approximately 19 epochs), Adam first-order optimization, and a learning rate of 0.001, which was halved after 1000 training iterations [31]. The authors experimented with dropout regularization in the fully-connected layer but determined that this technique was largely ineffective for the current application. The RGB images were randomly flipped horizontally during training with rates of 50% to introduce stochasticity and prevent overfitting. This method of data augmentation indirectly considered changes in camera orientation. Training was performed on a TITAN Xp graphics card (NVIDIA, USA) with 3840 core processors and 12-GB memory. Training took approximately 20 minutes/fold. The computational cost of the convolutional neural network was 1.75-G floating point operations.

III. Results

Fig. 5 presents the resulting multiclass confusion matrix, which displays the overall classification performance of the convolutional neural network. The horizontal and vertical axes characterize the predicted and actual classes, respectively. The diagonal elements represent the accuracy percentages of the individual environment predictions, also termed true positives. Nondiagonal elements are the misclassification percentages. The environment recognition system achieved 94.85% overall classification accuracy, that being the ratio of true positives (32,491) over total number of images (34,254). The precisions of level-ground, incline staircases, and decline staircases were 95.9%, 92.5%, and 87.3%, respectively. Precision denotes the proportion of true positives from the combined true positives and false positives. False positives for a given class were the values in the equivalent matrix column (i.e., excluding the true positive).

	Predicted Level-Ground	Predicted Incline Stairs	Predicted Decline Stairs
Actual Level-Ground	0.977	0.010	0.013
Actual Incline Stairs	0.108	0.887	0.005
Actual Decline Stairs	0.207	0.007	0.786

Fig. 5 The resulting multiclass confusion matrix of the environment recognition system.

The corresponding class sensitivities were 97.7%, 88.7%, and 78.6%. Sensitivity denotes the proportion of true positives from the combined true positives and false negatives. The false negatives for a given class were located in the corresponding row, excluding the true positive. The environment recognition system best predicted level-ground environments followed sequentially by incline staircases and decline staircases. These results are likely attributed to the class imbalances among the training dataset (i.e., there were many more images of level-ground environments). There were few misclassifications between incline staircases and decline staircases. Fig. 6 shows several examples of misclassifications from the environment recognition system. The photographs in the left and right columns were misclassified as level-ground and staircase environments, respectively.

IV. Discussion and Conclusion

The preliminary design and evaluation of an environment recognition system, using deep convolutional neural networks and machine vision, to supplement the predictive control of robotic lower-limb prostheses and exoskeletons was presented. Most biomechatronic devices have used individual finite state machine controls for different locomotion modes [5]-[6]. Automated locomotion mode recognition systems that facilitate more accurate and quicker transitioning between different locomotion modes are needed since inaccurate and/or delayed transitions could cause injuries [2]-[3], [22]. Most robotic lower-limb prostheses and exoskeletons have used electromechanical sensors and/or surface EMG for locomotion mode recognition [2], [4]-[6], [8], [11], [13], [16], [18]-[20]. Such measurements are patient-dependent, have limited prediction horizons, and are prone to intra-mode and inter-day differences.

Analogous to autonomous vehicles and robotics [24]-[25], few researchers have proposed supplementing neuromuscular-mechanical data measurements with knowledge about future walking environments [7], [9]-[10], [12], [14]-[16], [21]-[23]. The environment recognition system from Varol's research group achieved 94.1% overall classification accuracy using depth sensing images and support vector machines [7], [9]. In comparison, the environment recognition system presented here achieved 94.85% overall classification accuracy using RGB images and deep convolutional neural networks. Note that the class imbalances among the training dataset should be considered when evaluating the classification accuracy.

To the authors knowledge, this research represents the first documented investigation using deep learning for environment recognition to improve the predictive control of robotic lower-limb prostheses and exoskeletons. The convolutional neural network was trained to recognize three walking environments: level-ground, incline staircases, and decline staircases. Given that inaccurate and/or delayed locomotion mode transitions can cause serious injuries, particularly involving staircases, this research focused on recognizing staircase environments. Future research will incorporate other environment classes. For example, previous locomotion mode recognition systems have included: level-ground walking [2], [4], [7], [9]-[14], [16], [18]-[20], [22], ramp ascent [4], [10], [13]-[14], [18]-[20], [22], [26], ramp descent [4], [10], [13]-[14], [18]-[20], [22], [26], staircase ascent [2], [4], [7], [9]-[14], [16], [18]-[20], [22], [26], staircase descent [2], [4], [7], [9]-[14], [16],

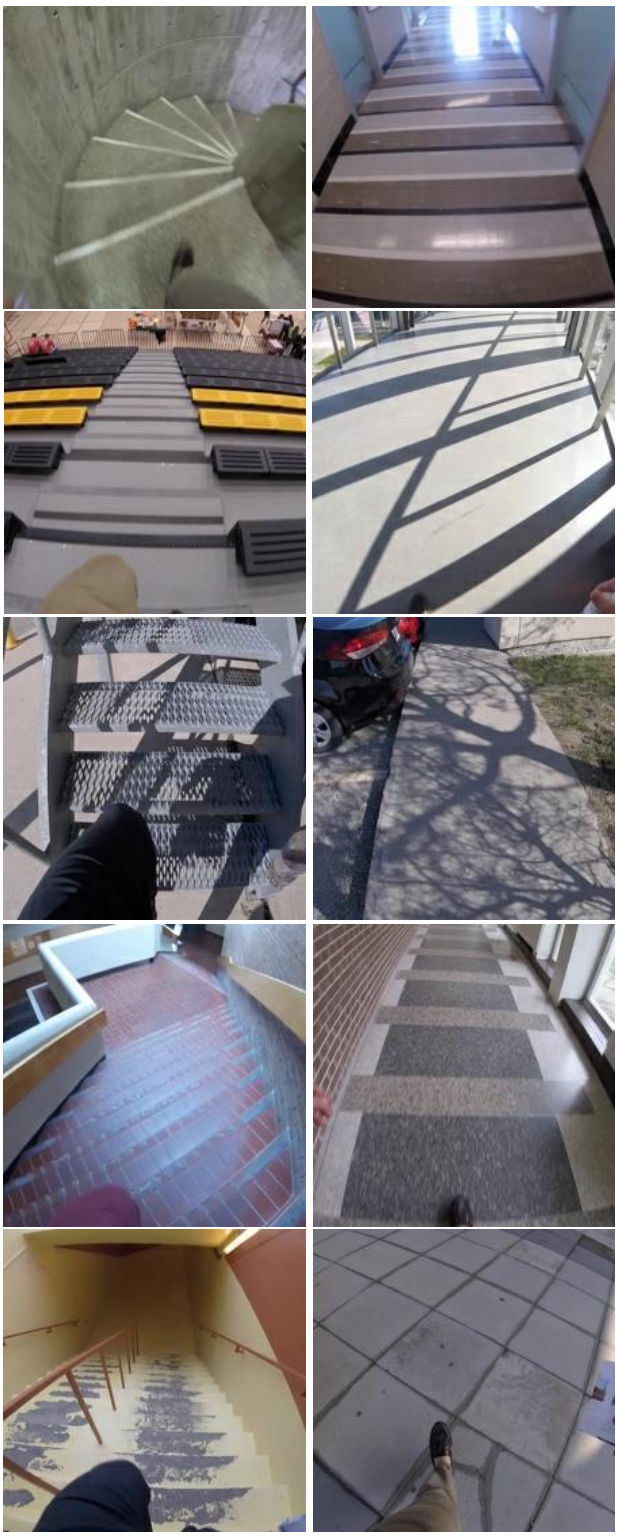

Fig. 6 Examples of misclassifications from the environment recognition system. The photographs in the left and right columns were misclassified as level-ground and staircase environments, respectively.

[18]-[20], [22], [26], standing [7], [9], [11], [15]-[16], [18], running [7], [9], and stepping over obstacles [11]-[13], [22].

Future environment information should be combined with electromechanical sensors and/or surface EMG for automated locomotion mode recognition. The environment recognition system updates the probabilities of selecting an individual locomotion mode [10], [15], [21]. For instance, when walking towards an incline staircase, the probabilities of selecting staircase ascent would progressively increase while the probabilities of selecting other locomotion modes would likewise decrease [15]. To further minimize the search space of potential solutions, locomotion modes with similar walking biomechanics (e.g., level-ground and slope descent) could be lumped together and uncommon locomotion mode transitions could be disregarded (e.g., slope descent to staircase ascent) [18], [20]. Therefore, future environment information would supplement, rather than replace, the locomotion mode control decisions from neuromuscular-mechanical data measurements [12], [14]-[15]. To date, no previous environment recognition system has been integrated into the physical control hardware of robotic lower-limb prostheses and exoskeletons while assisting geriatrics and rehabilitation patients.

Although convolutional neural networks are becoming the state-of-the-science in computer vision, the current embedded systems of robotic lower-limb prostheses and exoskeletons cannot effectively support the computational requirements associated with deep learning [7]. Compared to conventional microcontrollers with central processing units, the newly-developed graphics processing units have many more core processors, which permit faster computations through parallel computing and have higher memory bandwidths [27]. Several companies like NVIDIA and Intel Corporation are developing advanced microcontrollers for machine vision applications in autonomous vehicles and robotics [7], [27]. For instance, the Jetson Xavier microchip from NVIDIA can execute 30 trillion operations/second under 30 W. Nevertheless, most embedded systems for deep learning applications require significant amounts of computing power [7], [27], [32] and consequently would quickly deplete the onboard batteries of lower-limb biomechatronic devices. Furthermore, the lithium-ion batteries powering the current camera system provided only 1-2 hours of maximum operation, therein making systems integration with physical control hardware challenging.

Apart from technological advances in embedded systems, utilizing more efficient network architectures and/or optimal biomechatronic system dynamics might alleviate some of the large power requirements commonly associated with machine vision and deep learning. The authors are currently exploring more efficient deep convolutional neural networks for mobile vision applications, alike the architectures recently proposed by Google researchers [32]. Besides supplementing automated locomotion mode transitions, the environment recognition system could be used for improving overall energy-efficiency through optimal biomechatronic system dynamics. Analogous to eco-driving in autonomous and connected vehicles, future environment information could be used to optimally control the biomechatronic system dynamics to maintain more steady gait speeds, therein improving energy-efficiency by avoiding unnecessary power consumption from recurrent deceleration and acceleration periods [33]. Future investigations with the environment recognition system will be directed towards more energy-efficient control of robotic lower-limb prostheses and exoskeletons [34].

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