[0212] As described herein, the parameter optimization has been carried out by using only a small dataset (4 recordings out of a total of 78 recordings). As indicated by the results, the ability of the myoprocessors to accurately predict the joint moment increased significantly with an optimized set of internal parameters. While optimization on a large set of data can yield better results during testing, it may not be feasible to optimize the model on all the possible upper limb movements. Note that even with a relatively small database used for the optimization process, acceptable overall performance is achievable. A small optimization database yields a model able to perform reasonably well in a broad range of conditions.

[0213] For elbow movements, the results (see Table III) indicate that the integration of myoprocessors into a single neuromuscular model of the arm is capable of predicting the joint's torque with an average E_{rms} of about 8.6 Nm when parameters are not optimized. After optimization this prediction is improved to an average E_{rms} of 3.8 Nm. Moreover, after optimization, the percentage of time the absolute error stays below 4 Nm (η_4) is increased from an average 22% to an average 73%. Also for the wrist movements the E_{rms} is more than halved after optimization and η_4 shows an increase from 40% to 73%. The predictions for the elbow joint movements showed better correlation (ρ) with the reference torques compared to the wrist joint. In particular wrist extension movements presented on average a lower ρ after the optimization, even when all the other error measures consistently improved. An explanation for this phenomenon can be provided by considering that finger flexors and extensors significantly contribute to the wrist flexion-extension torque but these muscles were not included in the model. In the case of the elbow joint, all the relevant muscles for the flexion-extension movement were included, which may explain the better ρ.

[0214] Given the synergistic behavior of the physiological muscles and the fact that some muscle[s] were not accessible using noninvasive technique[s], the "maximum endurance of musculoskeletal function" criterion has been used for predicting the contribution of the BRA muscle. This technique can be extended beyond its current use to allow further reduction in the number of sEMG electrodes required for a satisfactory torque prediction.

[0215] Different myoprocessors are able to model muscles attached to the skeleton in different ways. Modeling more complicated cases in which the muscle wraps around several anatomical structures (multiple obstacles) requires more computational power than simpler conditions (single obstacle). By accounting for these constraints, myoprocessor complexity can be shaped to match the computational power available. One example allows the 12 myoprocessors to run simultaneously in real time with a maximum TET below 400 μs. One example can include approximately 20 myoprocessors modeling muscles of wrist, elbow, and shoulder joints and able to meet the real-time requirement of the exoskeleton main control loop (computational interval of 1000 μs).

[0216] The myoprocessor described herein provides a good balance between complexity and performance. Along with GAs for the optimization of the internal parameters for a specific user, an ensemble of myoprocessors can be used for an HMI that operates in real-time conditions.

[0217] The myoprocessor is a muscle model that performs real time processing of input signals, including the muscle activation level and joint kinematics, in order to predict the muscle force or the moments generated by a synergetic group of muscles e.g. flexor or extensor. The muscle activation level is defined as the percentage of the neural activity of the muscle during maximal isometric voluntary contraction. The algorithm for evaluating the normalized muscle activation level (FIG. **12**) can be used in the field of biomechanics and it is digitally implemented into the real-time control system. The algorithm includes: (i) a high-pass filter for filtering low frequency artifacts associated with the fact that the muscles are moving during their contraction; (ii) a full wave rectifier; (iii) a low-pass filter for calculating the signal's envelope and; (iv) signal normalization mapping the signal into the <0-1> range.

[0218] The myoprocessor processes the muscle's neural activation levels along with the joint kinematics to predict the muscle force (or moment with respect to a specific joint). This prediction is used by the exoskeleton system to generate the appropriate joint torque to assist the operator.

[0219] In one example, the I/O signals are used to identify the internal parameters of the both the Hill model (HM) and the artificial neural network (ANN). In terms of the HM both the force velocity (F-V) and the force length (F-L) function for various muscle activation can be identified. In addition to the HM, using the same I/O signals, a two layer ANN can be trained based on the data from, for example, 5 subjects.

IV. VARIOUS APPLICATIONS

[0220] The exoskeleton is an external structural mechanism with joints and links corresponding to those of the human body. Worn by the human, the exoskeleton transmits torques from proximally located actuators through rigid exoskeletal links to the human joints. The control algorithm used to operate the device can be configured to implement different modes of operations, including, for example, the following four: (1) a therapeutic and diagnostics device for physiotherapy, (2) an assistive (orthotic) device for human power amplifications, (3) a haptic device in virtual reality simulation, and (4) a master device for teleoperation.

[0221] The exoskeleton of the present subject matter can be controlled by a stroke patient, for example, while performing task-oriented occupational therapy activities in a virtual reality (VR) environment.

[0222] In one example, the present subject matter includes hand exoskeletons, each having 9-DOF which enable dexterous and power grasping.

[0223] According to one example, virtual reality (VR), or virtual environment (VE) technology provides an immersed experience typically involving audio and visual feedback perception for the user. Robotic devices can apply forces to a user through a mechanical interface and can therefore add the sense of touch (haptics) to the experience. The combination of audio-visual and force feedback enables the creation of detail rich, engaging virtual environments.

[0224] In one example, a computer operable program is configured for establishing and managing a virtual coupling between a haptic-configured exoskeleton device and a virtual environment or virtual reality. One example includes a virtual representation of a human body along with two fully