[0203] III. Results

[0204] During the first phase of the experimental recordings, flexion and extension movements of the elbow were performed; in a second phase, recordings were done during flexion and extension movements of the wrist. The kinematics (oint angles), dynamics [joint torques, estimated by using (Eq. 29)-(Eq. 27)], of the neural activation levels of some muscles can be graphically depicted as a function of time.

[0205] The angular joint positions and the neural activation levels of the muscles can be used as inputs to the myoprocessors. Some of the joint torques serve as a reference to optimize the model parameters; the remaining torque estimations have been used to assess the myoprocessor predictions. More specifically, the myoprocessor parameters of the FCU, FCR, ECRB, ECRL, and ECU muscles have been optimized by using repetition #2, 1.04-Kg load, flexion, and repetition #2, 1.04-Kg load, extension movements (thus, 2 recordings have been used during optimization and 22 during testing). The myoprocessor parameters of the BRD, BLH, BSH, TmH, TLgH, and TLtH, muscles have been optimized on repetition #2, medium velocity, medium weight, flexion movement, and repetition #2, medium velocity, medium weight, extension movements (thus, 2 recordings have been used during optimization and 52 during testing).

[0206] The performances of the myoprocessors during the test phase are summarized in Table III. The values presented refer to the metrics defined in (28)-(31). The results are averaged over the entire test dataset (test data have not been used for the model optimization).

TABLE III

AVERAGED RESULTS FOR THE TEST DATA SETS (MEAN AND STANDARD DEVIATION) BEFORE AND AFTER OPTIMIZATION FOR ELBOW FLEXION AND EXTENSION (EF, EE) AND WRIST FLEXION AND EXTENSION (WF, WE)

		E_{rme} [Nm]	E_{max} [Nm]	ρ	η_4	η_6
Non optimized	ef	8.1 ± 2.2	15.3 ± 3.9	0.8 ± 0.1	0.2 ± 0.2	0.4 ± 0.2
	ee	9.1 ± 2.3	15.9 ± 4.9	0.84 ± 0.10	0.24 ± 0.16	0.40 ± 0.18
	wf	0.40 ± 0.1	0.85 ± 0.15	0.86 ± 0.03	0.64 ± 0.28	0.85 ± 0.16
	we	1.53 ± 0.52	2.85 ± 0.92	0.70 ± 0.05	0.16 ± 0.10	0.24 ± 0.13
Optimized	ef	4.2 ± 0.97	11.0 ± 3.0	0.87 ± 0.05	0.67 ± 0.11	0.85 ± 0.09
	ee	3.4 ± 1.3	9.6 ± 4.1	0.89 ± 0.08	0.79 ± 0.15	0.91 ± 0.09
	wf	0.26 ± 0.17	0.64 ± 0.24	0.80 ± 0.05	0.83 ± 0.26	0.92 ± 0.14
	we	0.39 ± 0.16	0.75 ± 0.25	0.42 ± 0.46	0.63 ± 0.28	0.82 ± 0.21

Joint torques predicted by the myoprocessors after parameter optimization can be plotted. Each plot, for example, can include three torques: 1) the myoprocessor predictions with nominal model parameters (nonoptimized); 2) the reference torque as computed by using (23)-(27); 3) the myoprocessor predictions with optimized parameters.

[0207] A notable characteristic of the myoprocessors is their ability to work in real-time. Given a specific computational power, there is a balance between the complexity and number of the myoprocessors and the capability of the hardware system to perform in real-time. The task execution time (TET) of the myoprocessors system as a function of the number of muscles modeled can be visually presented. The TET was estimated simulating a flexion movement of the elbow, with angular position described by a saw-tooth spanning the 0-145 range of motion; other joints are held in a neutral position; neural input was held constant at an activation level of 0.5 (50% of the maximal voluntary activation level). The saw-tooth had a period of 1 second. Max, min, and averages values are measured in 30-s time slots.

[0208] In one example, the hardware platform includes a PC104 with an Intel Pentium4 operating at 2.4 GHz processor and 512 Mb RAM. Nonlinearity of the TET as a function of muscle number can be observed, as a results of the different complexity of myoprocessors modeling different muscle.

IV. DISCUSSION

[0209] This document presents the development, optimization, and integration of real-time myoprocessors as a HMI for an upper limb powered exoskeleton. As one element of a neural controlled exoskeleton, the myoprocessors provide robust, accurate joint torque predictions over a broad range of loading and motion conditions.

[0210] Both black-box and white-box approaches can be used for muscle modeling. One example used an approach in which most of the internal parameters of the myoprocessor are directly related to physiological muscle parameters. More specifically, one example of the myoprocessor includes a Hill-based muscle model together with a three-dimensional anatomical representation of the upper limb and a nonlinear sEMG-to-Activation signal processor. In addition, GAs are used to optimize the myoprocessor's internal parameters, for each specific subject wearing the exoskeleton, without the need for a priori exact knowledge of each muscle parameter. The optimization is constrained in order to prevent parameters from exceeding physiological ranges.

[0211] By some measures, the resulting model has more characteristics in common with white-box models than with black-box models (e.g., neural networks), even if the adherence to physiology of the model can be improved at several levels: some elements, such as muscle pennation, can be included in the model structure; the optimization boundaries for each parameter can be different for each muscle in order to exploit all the knowledge available for the different muscles; the Hill model and the kinematic (skeletal) model can be optimized in an intertwined way that, for example, a change in the origin or insertion point of a muscle, will be reflected in a corresponding change of tendon slack length and optimal fiber length.