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Muscle-Synergy for Human-Robot Control, Wearable Devices and Computer Animation: A Survey

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ABSTRACT

Known studies in neurosciences have discovered that locomotion or motor tasks in humans involve the central nervous system (CNS) to manage activation signals for several groups of muscles. The CNS produces coordinated activation patterns, known as muscle synergy, that reduce the number of control signals by combining them into sets of activation signals. Muscle synergy is possible to be observed via electromyography (EMG) and can be extracted from the EMG data through factorization. As several factorization methods can be used to extract muscle synergies, non-negative matrix factorization (NMF) was suggested best for active tasks. While the concept of muscle synergy has been adapted in various disciplines such as healthcare, engineering and computer graphics, this narrative review discusses how muscle synergy has benefited them. Application involving muscle synergies is presented that focuses on muscular rehabilitation, human-robot control, prostheses assistive devices and graphical animation. Finally, future research is conjectured about technical challenges and prospects of muscle synergy.

Keywords:

Muscle synergies; muscle control; electromyography; motor modules; robotics; character animation

1. Introduction

Generating a movement involves a great amount of work for the central nervous system (CNS). The CNS must handle thousands of coordinated signals for hundreds of motor units within the skeletal muscles. To achieve the intended movement, the CNS has to specify a great number of output variables and must also consider various biomechanical constraints during movement execution, including muscle strength, muscle stiffness and neuromotor reflex gains [1]. There exist works that are replicating the CNS to control the human movements during fatigue [2-4]. Hence, muscle signals for movement in a small child can be very different compared to an adult due to the difference in the biomechanical design of their limbs. As the body develops and learns new difficult

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skills with different kinetic, kinematic or energetic requirements, the CNS would need to acquire new muscle coordination patterns.

Many research has suggested that the human locomotion or motor task is the result of synergized contraction of several collections of muscles, where the CNS produces persistent, synchronized movements in interaction with the rest of the body [5-8]. Since the range of muscles contributing to a movement widely varies depending on the task constraints of the movement, neuroscientists suggested that the CNS act as the motor control in charge of determining the timing and activation levels of the involved set of muscles to work in synergy [9]. The muscle synergy concept was acknowledged as the mechanism utilized in the CNS to reduce the number of control signals by building and combining sets of activation signals [5]. As the concept of muscle synergy is already well known in neurosciences, other disciplines have opened up to adapting the theory such as healthcare, engineering and computer graphics.

To shed more light on the adaptation of muscle synergy theory, this review aims to explore the use case of muscle synergy in various fields. In our opinion, it is interesting to explore how muscle synergy is being benefited in various fields especially other than neurosciences. In this review, we provide a concise discussion of the theoretical model of muscle synergies and summarize the computational techniques employed for the estimation and extraction. A comprehensive overview of applications utilizing muscle synergies is presented, with particular emphasis on muscular rehabilitation, human-robot interaction and computer animation. Finally, we address the technical challenges and explore the future research direction in the field of muscle synergies.

2. Muscle Synergies: Theoretical Background

Over the past decades, various modular mechanisms have been theorized as means of controlling muscles for movement; e.g. spinal force fields [10], neuromotor synergies [11] and unit burst generators [12]. However, muscle synergy theory has become more evident by newer computational approaches and experimental evidence. There are strong evidences that shows muscle synergy as a physiological model implemented by the CNS to adaptively reduce the signal processing of motor output by generating optimized muscle signal patterns [1,13,14]. The low dimensional units of synergized muscle can be observed at the spine or muscles using electromyography (EMG) during movements [14]. Additionally, the synergy muscle's low dimensionality allows the CNS to be flexible in generating various signal patterns on a huge capacity with some synergy patterns being task-specific, whilst some patterns are linked with several other motor tasks [14]. Working mutually with sensory feedback, the CNS is able to regulate the generation of muscle synergies to adjust motor output based on the external environment depicted in Figure 1.

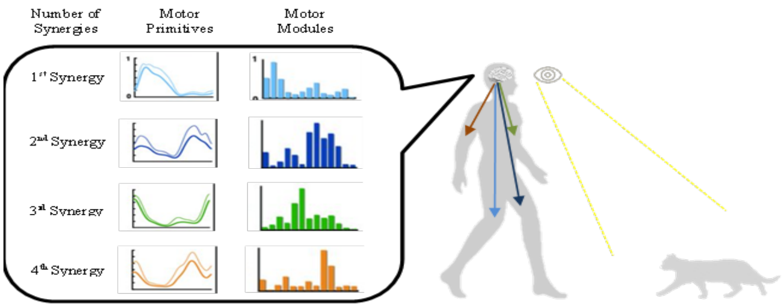

Fig. 1. A depiction example of muscle synergy concept in human that comprises of number of motor primitives, motor modules and sensory feedback to modulate the recruitment of muscle synergies [15]

The conventional approach to extracting the muscle activation patterns is by distinguishing recurrent EMG patterns from several muscles during movement. In synergy extraction, a large number of muscle activities for a motor task are decomposed into a smaller amount of activation signal patterns with associated weights, known as muscle synergy vectors (W) and temporal activation patterns (C) [1]. Extraction of muscle synergies is possible by factorizing the data acquired from EMG signals, which proceeds to the calculation of muscle synergy vectors; a time-independent matrix that contains the weights contribution of each muscle to a specific synergy and temporal activation patterns; a time-dependent waveform that denotes the modulating excitation signal of the specific synergy. A vector containing the muscle activation patterns E(t) is constructed by concatenating the EMG data for the total exercise and generating a model based on the linear combination of synergies:

$$E(t) = \sum_{i=1}^{N} W_i C_i(t - t_i) \tag{1}$$

Where $E(t)$ is defined as a vector of time-dependent muscles activation recorded at a certain time or time interval $(t - t_i)$, N is the number of synergies selected, Wi is a vector of time-independent muscle modules that weight the synergy and C_i is the motor primitives, which is a time-dependent coefficient vector. The principal component analysis (PCA), independent component analysis (ICA), factor analysis (FA) and non-negative matrix factorization (NMF) are the most used factorization methods for extracting the muscles' synergistic effects using second or higher order statistics to calculate the muscle synergies.

2.1 Principal Component Analysis (PCA)

The basis of the PCA method is to compress the dimensions of a dataset, while maintaining as much variability as possible, to generate new uncorrelated variables. This method works well with Gaussian distributed datasets; thus, it is great at extracting the best data variances that represent muscle synergy while using singular value decomposition to minimize the basis factor, which returns the eigenvectors of the data’s covariance matrix (muscle synergy weights) [16]. The PCA-based algorithm had been used to extract kinematic synergies in several studies involving hand grasping [17,18]. However, the limitation of the PCA is it is lack of non-negative constraints [69].

2.2 Independent Component Analysis (ICA)

Unlike the PCA extraction method, which compresses multiple pieces of information into a single dataset, ICA is a method of extracting individual information from a mixture of datasets [19]. ICA works best with non-Gaussian distributed datasets and involves data that is uncorrelated and independent. Therefore, ICA is often used in biomedical signal processing to remove noise and movement artifacts before proceeding to signal analysis [20]. For muscle synergy, mixtures of EMG signals can be separated using ICA where the basis vectors can be distinguished (i.e. muscle synergy weights) [21]. However, the limitation of the ICA is, it may result in overfitting when applied to small datasets which can produce components that are not physiologically relevant [70].

2.3 Factor Analysis (FA)

Factor analysis allows the determination of basic vectors of a matrix. Similar to PCA, FA can be used to extract muscle synergy weights by utilizing the decomposition of eigenvalues to produce eigenvectors of the covariance matrix. The significant muscle synergies are distinguished by their eigenvalues >1 and all eigenvalues of the synergies < 1 are deemed as noise [22]. Factor analysis allowed muscles with similar EMG linear envelopes to be clustered together in an objective approach. However, similar as ICA, FA requires large datasets to ensure that it can achieves the high level of accuracy [71].

2.4 Nonnegative Matrix Factorization (NNMF)

NNMF is the most common method of extracting muscle synergy since its optimization algorithm's linear decomposition properties minimize the reconstruction error [23]. As the name indicates, NNMF restrains muscle synergies to always be positive or zero, then utilizes second-order statistics to pick out vectors that are closest in defining the data's variance. The method utilizes the multiplicative update algorithm based on gradient descent algorithm [24], Euclidean distance objective function [25] and alternating least squares algorithm [26], all of which have evolution and convergence properties that can be applied to both Gaussian and non-Gaussian datasets [27]. NMF is preferred over other methods due to its simplicity in identifying the synergy vectors and activation signals. Its nonnegative properties allow easier interpretation of the synergy structure and are physiologically more meaningful, especially in clinical environments where qualitative interpretability is preferred. NMF has been proposed as the best for identifying muscle synergies during active tasks [28]. However, NNMF is known in its difficulty in modelling temporal dynamics [72]. The summary of the advantages and limitations for PCA, ICA, FA and NNMF can be seen in Table 1.

Table 1
Advantages and limitations of PCA, ICA, FA and NNMF

Factorization Methods	Advantages	Limitations
Principle component analysis (PCA)	It is great at extracting the best data variances that represent muscle synergy while using singular value decomposition to minimize the basis factor, which returns the eigenvectors of the data's covariance matrix (muscle synergy weights) [16].	Lack of non-negative constraints [69].
Independent component analysis (ICA)	Able to extract individual information from a mixture of datasets [19].	May results in overfitting when applied to small datasets which can produce components that are not physiologically relevant [70].
Factor analysis (FA)	Factor analysis allowed muscles with similar EMG linear envelopes to be clustered together in an objective approach.	FA requires large datasets to ensure that it can achieves the high level of accuracy [71]
Nonnegative matrix factorization (NNMF)	NMF is preferred over other methods due to its simplicity in identifying the synergy vectors and activation signals. Its nonnegative properties allow easier interpretation of the synergy structure and are physiologically more meaningful, especially in clinical environments where qualitative interpretability is preferred.	NNMF is known in its difficulty in modelling temporal dynamics [72].

3. Muscle Synergy Applications

Muscle synergy has been applied in various applications such as rehabilitation, human robot control, wearable assistive device control and recently, in computer animation. In rehabilitation application, muscle synergy analysis has been utilized in many neurorehabilitation applications where the EMG decompositions were used as biomarkers for functional rehabilitation training [19,20]. The neurorehabilitation training employs the quality of muscle synergies to visualize the potential effects of rehabilitation methods.

For neurological or muscular disorders, muscle synergy was used to study the compensational effects of different muscles. By analysing muscle synergy during fatigue, a study discovered that the trunk muscles are able to compensate for fatigue or atypical coupling in the arm for improved control [21]. These studies suggested that the CNS compensates by reassigning new sets of muscle control signals in patients with a neurological or muscular disorder.

Several studies have investigated physiological processes which cause motor symptoms and the dopaminergic therapy effects on muscle synergies in Parkinson's Disease patients [22,23]. These studies observed that the use of L-Dopa for motor symptoms has a low effect on muscle synergies during balance and movement, which suggests a physiological pathology involvement of non-dopaminergic pathways. Muscle synergy analysis from these studies provides important data on the physiology of specific motor symptoms such as balance, walking and upper limb movements of Parkinson's Disease patients.

Several studies have used muscle synergies analysis to improve rehabilitation strategies. Irastorza-Landa *et al.,* [24] proposed a reliable biomarker of motor function using the synergy recruitment index for chronic stroke patients. The study demonstrated that targeting proprioceptive therapies to their functional synergy recruitment index can enhance effective rehabilitation. Scalona *et al.,* [6] suggested that the consistency of real muscle synergy is similar to the virtual reality throwing tasks [7]. The study implies that virtual reality provides an alternative to conventional therapy which creates a viable method in rehabilitation programs related to muscle control recovery.

In human-robot control, muscle synergy has been applied for remote operation. For remote operations, a teleoperation robotic system is used in conditions where it would be difficult or dangerous for humans to perform, such as handling radioactive material in nuclear decommissioning or handling dangerous substances in laboratories. However, control for intricate motion is difficult to achieve, thus manual control is often preferred. There are a variety of human-robot interfaces for robotic teleoperation systems that utilizes control sticks, knobs and robotic end effectors that mimic a hand [26]. A robotic hand can offer the dexterity and manipulation capability to its user remotely. However, these machines can be unwieldy where it requires unnatural arm or hand motion. However, compared to human hands, the motion of the traditional robotic hand is limited by the number of joints it has and the type of motion the controller can produce. Hence, muscle synergies have been implemented in the field of robotics to deliver more intuitive control and allow the controllers to better adapt to the movement of a real human hand.

Muscle synergy has been the focus for myoelectric control for robotic application [27-31]. The low dimensionality of muscle synergy can be exploited into robotic control systems to accomplish human-like movements. Control method by Camardella *et al.,* [27] revealed that their synergy-based approach minimized performance loss across various working conditions, where force tasks were accomplished through a virtual online cursor. Similarly, by utilising muscle synergy, Selvaggio and Notomista [28] were able to control a swarm of robots intuitively and naturally. Kim *et al.,* [29] investigated how a robotic hand can be controlled from a human motion via electromyography (EMG) in a teleoperation system. The study implemented a multi-factor model to extract EMG synergy and mapped it to a robot hand. The study established that the method produced high postural accuracy and enabled dexterous manipulation of the robot hand remotely. A similar study assessed the feasibility of multi-DOF robotic control using a synergy-based approach for application in a realistic and clinically oriented framework [30]. The study stands out from previous work due to its higher number of muscles involved, which typically use only one agonistic and antagonistic muscle pair. It was shown that users can intuitively and easily control the myoelectric interface simply by using muscle contractions.

It is known that wearable assistive devices intend to augment the user's body either to increase limb performance, assist weak limbs or substitute missing limbs. Exoskeletons are wearable assistive devices acting in parallel to the body structures [32]. However, intrinsic difficulties with these devices such as mix actuator dynamics, muscle fatigue and actuator redundancy make it difficult to control. Muscle synergy has been implemented in designing hybrid robotic exoskeletons, which integrate neuromuscular stimulations with the exoskeletons to provide controlled movement of the device [33,34]. Controlling exoskeletons via muscle synergy can ensure that the exoskeleton receives an ideal input signal so that the actuators can safely provide optimal force to the wearer's body. Since an active exoskeleton requires actuators such as pneumatic artificial muscle (PAM) or electric motors, the control process of the actuation force can be precisely directed via synergy control. Such adaptive controllers have been utilized by using the synergy of agonistic muscle pairs to control the upper limb movement of a pneumatic exoskeleton and assisted leg movements in different gait phases [35,36]. Muscle synergy controller for exoskeleton can provide good trajectory tracking as well as compensating actuator redundancy and muscle fatigue [37].

On the other hand, prostheses are wearable devices designed to restore normal body functions by replacing the missing body part [38,39]. Since muscle synergy provides a simpler interpretation of multiple muscle signals, it has the benefits of precisely controlling prostheses since it gives a better sense of the whole muscle motor control. Compared to a teleoperated robotic hand that mimics existing limbs, a prosthesis substitutes the missing body parts. Hence, the prosthesis controller needs to adapt muscle signals generated from the adjoining body parts. A study by Wilhelms [41] developed a controller that combines artificial vision and proprioceptive information in transradial prosthesis control, which resulted in a better myoelectric interface when controlling the prosthesis movements. The controller allows the prosthesis hand grasping motion to mimic the user's postural and hand stiffness in real-time. In addition, Scalona *et al.,* [6] assessed controllers for a synergy-inspired prosthetic hand and found that a differential electromyography-to-position mapping technique ensured the highest coherence of prosthesis with hand movements. The design of active prostheses with integrated muscle synergies in the controller may allow for better prostheses control.

Computer animation is part of the computer graphics area. Computer animation in a typical computer graphics application involves characters and objects interacting with each other in a virtual environment where the character's animation is done by either kinematic-based or physics-based methods. Although kinematic-based animation databases have improved over the years, this method lacks the capability to generate realistic and natural responsive animation due to the restricted contents of the motion database. Alternatively, physics-based character animation has the advantage of generating realistic responses. This method involves a physics simulation process, which consequently results in physically accurate interaction without using additional motion data [41]. Physics-based animation can simulate realistic phenomena, such as character collapsing (e.g. ragdoll) [42,43], draping cloth [44] and flowing fluids [45,46]. However, physics-based characters are underactuated or lack controllability because the character is controlled indirectly through external contacts and forces acting on the character. Under actuation creates an issue that affects visual quality that reduces the realism of the animation. A virtual character with a musculoskeletal system can resolve the underactuated problem by generating muscle actuation similar to an actual human [7].

Coordinated muscle activation has been adapted in many computer graphics applications as controllers for limb movement in character animation [18,48-52]. This application follows the same principle as the human-robot interaction where muscle signals are applied to a controller for the mechanical devices, i.e. robots and prostheses. In animation, the signal for control is delivered to the virtual musculoskeletal models, where the musculoskeletal model consists of segments, joints, masses, inertias and actuation capacities that are modelled in a convenient way to enable physical simulation [52]. Human gait has been accurately simulated by modelling the spinal muscle control involving synergized muscle signals that includes reflex-based balance controllers [53]. Such controllers produced different gait simulation patterns including nominal and disturbed. Directly controlling the motion of a musculoskeletal system in a character via muscle synergy is possible as demonstrated in a throwing experiment [54,55]. The muscle synergies during actual throwing motion were extracted following the NMF protocol, which is then matched to the musculoskeletal character. The results accurately reproduced animated motions using simplified muscular structure while preserving important characteristics of the original synergies.

Several studies have shown that deep learning can generate muscle patterns that produce realistic motion for a character which is driven by muscle contraction dynamics [18,52,56]. For example, Lee *et al.,* [18] have developed a scalable imitation learning algorithm that can control a musculoskeletal model that has 346 muscles. The study showed that the learning algorithm is able to predict dynamic motor skills under anatomical constraints and simulate several pathological gaits. However, the study's main attention is on producing natural motion without accurately representing the underlying biological system. Even though generated motion using deep learning can be convincingly accurate, the generated muscle patterns are an estimation from a learned motion which may lead to unnatural or infeasible torque patterns for real humans to achieve [57]. Table 2 summarizes the application of synergized movement involving muscles including number of subjects involved and method of determining synergy that has been presented.

Table 2
Muscle synergy application in rehabilitation, human – robot control, wearable devices and computer animation

Field	Author	Synergy Application	Subject	Synergy method
Neuro Rehabilitation	[24]	Eliciting correct temporal recruitment patterns of common functional synergies.	18 Chronic stroke patients	NNMF
	[19]	Evaluate longitudinal changes in the modular motor coordination during leg-cycling	12 Stroke patients	NNMF
	[20]	Synergy based Functional Electrical Stimulation for post-stroke rehabilitation of upper-limb functions.	6 Chronic stroke patients	NNMF
	[21]	Detection of fatigue compensation during upper limb rehabilitation training.	8 Healthy Subjects	Joint Angle Synergies
	[22]	Analyse the changes of muscle activation during resting tremor and voluntary movements evoked by cutaneous stimulation.	3 Parkinson's Disease patients	NNMF
	[23]	Investigate changes in postural control during upright stance using muscle synergies.	10 Parkinson's Disease patients	NNMF
	[6]	Evaluate muscle synergies of VR task with actual throwing task.	17 Healthy Subjects	NNMF
Human-robot control	[27]	Synergies-to-force mapping of a upper limb pose	5 Healthy Subjects	NNMF
	[28]	Control for human-swarm teleoperation to accomplish grasping and manipulating tasks	1 Healthy Subject	PCA
	[29]	Tele-operated robot hand controller.	5 Healthy Subjects	Multi-factor Mode
	[30]	Multi-DOF robotic control compared to the simple muscle-pair method.	8 Healthy Subjects	DOF-wise NNMF
	[31]	Equilibrium points-based synergy for control of anthropomorphic legs with PAM.	1 Healthy Subject	Agonist-Antagonist muscle pairs
	[73]	Used to design exoskeletons to assists patients with impaired motor controls such as stroke patients	8 Healthy subjects	ICA and NNMF
	[74]	Muscle synergies are applied to the control of powered ankle exoskeletons.	9 Healthy subjects	Gait
Wearable assistive device control	[35]	Man-Machine Synergy Control	1 healthy subject	Agonist-Antagonist muscle pairs
	[36]	Adaptive synergy-based controller for lower-limb exoskeleton.	3 healthy subjects	Agonist-Antagonist muscle pairs
	[37]	Hybrid neuroprostheses synergy-based controller	1 Healthy Subject 1 spinal injured subject	PCA
	[40]	Vibro tactile feedback scheme that transmits variables to the control of multifunction prosthesis.	5 amputees subjects	Tactile feedback
	[75]	Isometric upper-extremity task	No live subjects involved	Upper-extremity isometric force task

	[76]	To analyse the EMG signals as an input signal in the prosthesis, virtual interface and rehabilitation	10 healthy subjects	Hierarchical alternating least square (HALS)
Computer Animation	[50]	Simulation of Spinal Muscle Control in human gait	No live subjects involved	CPG
	[7]	Motor control model based on muscle synergy hypothesis	1 healthy subject	CPG
	[18]	Human Simulation Control	No live subjects involved	Deep Reinforcement Learning DRL
	[14]	Control for virtual character throwing motion	1 Healthy Subject	NNMF
	[47]	Using CPG to induce muscle contraction of the virtual swimmer's body.	No live subjects involved	Central pattern generators CPG
	[77]	To animate a realistic hand avatar with 20 degrees of freedoms(DOFs) based on the biomechanics of the human hand.	No live subjects involved	Kinematics
	[78]	To generate muscle activation controls or joint torque	1 high-functioning hemiparetic male induvial with chronic stroke-related walking dysfunction	Inverse kinematics

4. Discussion

The principle of muscle synergy has been adapted in various applications since the low dimensionality of the complex muscle system can be practically utilized. However, muscle synergies can be challenging to extract because it requires extracting EMG signals from different muscles in the body. As the human body has over 300 pairs of skeletal muscles, defining all the muscles involved in a motor task is very complicated [58]. Hardware is one of the limitations as EMG sensors are often limited in the number of sensors the hardware can handle. In addition, attachment points for surface EMG are limited since they are only effective in detecting superficial and large muscles that are closer to the skin surface [59]. While Invasive EMG can record signals of deep muscles (i.e. psoas and iliacus) using intramuscular wire sensors, a small movement of the wire electrode can easily introduce motion artifacts during contraction [60]. Therefore, it is typical that muscle synergy is extracted only from the dominant muscles involved in the task; i.e. for a throwing action, EMG is taken only from the upper limbs such as deltoids, biceps and triceps, even though other muscles of the body such as the hip muscles also contribute to the action.

Machine learning is a powerful tool in developing neuromechanical control models. A recent study reported that learning the controller is time consuming, ranging from 12 to 36 hours of computation time [18]. As more technological advancement becomes accessible, computing complex problems would be more convenient to solve. With better computing capability, it would increase machine learning efficiency and could create a better tool to rapidly synthesize appropriate activation patterns. There are plenty of machine learning research that focus on net behavioural effects, however realistic motion seems to be the main focus of these research that is short of considering the underlying neuromechanical properties [61]. There are also human locomotion models that incorporate simple dynamic models and data-driven mathematical models which enlighten the dynamic principles of walking and running [62]. Implementing these learning models together with muscle synergy motion control could provide a holistic evaluation of both motor control as well as learning models.

Regarding computer animation, an animated character is preferred to be driven kinematically with physical properties, due to its relatively convincing visuals with lesser variables and computational power demand compared to muscle-based animation. However, it does not represent actual physiology and would benefit less in understanding muscle functions. As computational capacity is rapidly growing, the notion of realistically and accurately animating a character by activation of many muscles may be plausible. The implementation can be done in a graphical environment by modulating the contributions of a small set of predefined muscle variables. The dimension reduction properties of muscle synergies have the benefit of increasing the computational efficiency of the control algorithm for animating the musculoskeletal system on the characters to broader areas such as surgical planning and training [64], education [64,68] and also forensic use cases [65]. The increased interest in accurate and realistic virtual characters particularly in producing muscle-based character animation is because muscle-based actuation provides better estimates of energy expenditure [66], better character stability properties [67], provides better character control and allows simulation of muscle defects and fatigue.

5. Conclusion

Knowledge of the complex neural signals of the CNS to control muscle in motor tasks gains attention in various fields. The extraction of muscle synergy has been shown useful in optimizing rehabilitation training which improves rehabilitation strategies. Muscle synergy has shown useful as a controller for teleoperated and muscle-like actuated robots, as well as a controller for wearable assistive devices such as prostheses and exoskeletons. Muscle synergy has also been adapted as a controller for a virtual character's animation, although its application is rarely to be found. This review delivers insight into tangible muscle synergies application in the different fields of healthcare, robotics and computer graphics. Although it is known that muscle synergies are applied more in human-robot control and wearable devices, based on the review, muscle synergy also can be applied in computer animation, specifically in character animation. However, the progress of the work is still ongoing. Therefore, this opens the opportunity for future endeavours to explore new applications involving muscle synergy.

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