Artificial Intelligence Review (2021) 54:1507–1523
https://doi.org/10.1007/s10462-020-09885-8

Artificial intelligence based on fuzzy logic for the analysis of human movement in healthy people: a systematic review

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Published online: 1 August 2020

Abstract

Technological advances that involve computing and artificial intelligence (AI) have led to advances in analysis methods. Fuzzy logic (FL) serves as a qualitative interpretation tool for AI. The objective of this systematic review is to investigate the methods of human movement (HM) analysis using AI through FL to understand the characteristics of the movement of healthy people. To identify relevant studies published up to April 19, 2019, we conducted a study of the PubMed, Scopus, ScienceDirect, and IEEE Xplore databases. We included studies that evaluated HM through AI using FL in healthy people. A total of 951 articles were examined, of which six were selected because they met the criteria presented in the methods. The protocols had high heterogeneity, yet all articles selected presented statistically satisfactory results, in addition to low errors or a false positive index. Only one selected article presented protocol applicability within the free-living model. Generally, AI using FL is a good tool to help assess HM in healthy people, but the model still needs new data acquisition entries to make it applicability within the free-living model.

Keywords Artificial intelligence · Fuzzy logic · Analysis · Human movement · Systematic review · Review

Abbreviations

AI	Artificial intelligence
FL	Fuzzy logic
HM	Human movement
ANNs	Artificial neural networks
MUs	Motor units
MUAP	Motor units action potential
EMG	Electromyography

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1 Contributions to the literature

- Research involving AI is proving to be a promising branch for faster and more accurate diagnostics. Differences in diagnosis regarding biological intelligence are caused by the high accuracy of AI.
- The development of AI depends on computational technologies and new forms of implementation, but AI is already presented as an accurate response tool for the analysis of HM.
- FL is a tool that allows AI to approximate biological intelligence and it incorporates qualitative responses to process an uncertain margin.

2 Introduction

The analysis of human movement (HM) is undergoing changes because of access to technologies that use different methods of artificial intelligence (AI). Thus, the development of solutions that can learn to analyze, evaluate, diagnose, and prescribe appropriate highly personalized movement is feasible (Akash et al. 2018; Bastawrous et al. 2018; Cust et al. 2019; Kermany et al. 2018; Montoye et al. 2016; Mostafa et al. 2018; Sarowar 2018). Human performance is typically subjective, and subject to errors and bias. The use of AI in the recognition of HM has the potential to improve both the efficiency and accuracy of the analysis of characteristics evaluated using data inputs that are obtained through biomechanical analysis equipment, such as inertial measurement units (IMUs) (accelerometry), view (cinemetry) and electromyography (EMG) (Akash et al. 2018; Bastawrous et al. 2018; Cust et al. 2019; Kermany et al. 2018; Montoye et al. 2016; Mostafa et al. 2018; Sarowar 2018). New technologies improve communication between devices that have such a purpose, thereby enabling greater interaction with human users. Small devices with good precision are easy to carry, which can make wearable technologies part of the routine for people who have access to this technology (Akash et al. 2018; Bastawrous et al. 2018; Kermany et al. 2018; Montoye et al. 2016; Mostafa et al. 2018; Sarowar 2018). Improving the accuracy and speed of decision making for assessing tasks in various types of environments is an important purpose of AI (Cippitelli et al. 2016; Cust et al. 2019; Manoj and Thyagaraju 2018; Montoye et al. 2016; Mostafa et al. 2018).

AI is linked to technology and can be present in any device that has processing power that is compatible with the related software (Pan 2016). The evolution of AI depends on the development of new technologies and demands that lead to the implementation of new algorithms (Montoye et al. 2016; Pan 2016).

The architecture of AI is based on three nodes: the input (data acquisition), processing, and output. Processing is performed by an algorithm that interprets the input (data acquisition) and generates an output. Each algorithm represents an artificial neuron that, together with others, creates a complex processing network called an artificial neural network (ANN) (Ahn 2018; Calmet and Campbell 2010). A system of ANNs, fed by new algorithms, becomes more assertive than before in decision making (McBee et al. 2018). The development of knowledge about innumerable phenomena that can be calculated can be transformed into algorithms (artificial neurons) that feed the ANNs. This process improves the capability of AI problem-solving (McBee et al. 2018).

The concept of assisted reality in intelligent and interconnected environments through AI is linked to the identification of the diversity of HM (Baca et al. 2009; Cippitelli et al. 2016; Manoj and Thyagaraju 2018; Mostafa et al. 2018). Posture assessment is an example of an activity that could be monitored in this type of environment, where the data can identify possible excesses or care needs for certain structures of the human body by identifying patterns that involving the position of body segments (Garza-Rodríguez et al. 2018; Golabchi et al. 2017; Savino et al. 2017).

Computational advancement is helpful as a tool for sporting skills development protocols, where the use of AI is also useful for increasing the accuracy of sports practitioners' assessments for slow, medium and fast responses (Baca et al. 2009). Recent studies have demonstrated the efficiency of using AI to understand the performance of athletes (Ahamed et al. 2017; Morales-Orcajo et al. 2018).

Fuzzy logic (FL) is based on approximate sets and flexible sets that are approximated using the functional floatability standards of biological intelligence (Deshpande and Kumar 2018). FL can process calculations that deal with uncertainties and inaccuracies, and is a qualitative approach to interpret numerical data (Ahmadi et al. 2018; Ma et al. 2017; Sakthivel et al. 2018). Recent studies have demonstrated several useful resources for AI applied to human health because it can accurately interpret and develop data that involve risks to human health (Ahmadi et al. 2018; 2018; Sarowar 2018). The junction of AI and FL has been highly precise in the processing of data collected using non-invasive techniques in the analysis of HM (Peulic et al. 2018).

Fuzzy set theory is based on mathematical calculations that involve the general theory of groups, where each group is formed by a class that has characteristics in common. Each class has characteristics based on values between 0 and 1 to calculate possibilities that could be considered uncertain (Sakthivel et al. 2018). The degree of matching between possibilities can be assessed simply based on the lower and upper bounds of the occurrence of the event studied (Sakthivel et al. 2018). Handing over fuzzy events to a simple mathematical language makes FL a tool for AI in assessing the inaccurate complexity of HM.

AI using LF is highly accurate in recognizing human locomotor patterns to identify musculoskeletal disorders, where locomotion pattern screening models analyzed by intelligent agents using LF as a tool can achieve great diagnostic accuracy (Farzandipour et al. 2018). However, even though there have been advances in studies on musculoskeletal disease patterns, the literature still lacks review data that can identify how human locomotor patterns were determined in research assessed by AI using LF aimed at healthy people.

The objective of this study is to perform a systematic review that investigates methods of HM analysis using AI through FL, with a focus on understanding the characteristics of the movement of healthy people. The purpose of this review is to answer the following questions based on AI using FL: (1) What motor gestures were used to assess the HM of healthy people? (2) What data collection equipment was used to generate the input (data acquisition)? (3) Were the results statistically satisfactory in assessing the HM of healthy people? (4) Do the control types used allow applicability within the free-living model? (5) What was the reason for choosing FL for the study?

Table 1 Keyword search terms by database

Keywords by database
PubMed; ScienceDirect; IEEE Xplore
(((fuzzy) AND artificial intelligence) AND human movement) AND biomechanics
Scopus
fuzzy AND artificial intelligence AND human movement AND biomechanics

Table 2 Inclusion and exclusion criteria of the study

Inclusion criteria	Exclusion criteria
Original article published and found from the guidelines described in Table 01	Articles published after April 20, 2019 or as of this date
Sample based on voluntary human locomotor movement of healthy people	Analysis of HM only investigated for clinical purposes
Research in the field of technology use	Activities aimed at investigating human behavior in the field of psychology
Development or use of learning algorithms to recognize HM	Main investigation linked to the trajectory of the ball or other projectile
Published as full studies written in English	Review studies
	Books and theses

3 Methods

A search for articles was conducted on the PubMed, Scopus, ScienceDirect, and IEEE Xplore databases to identify relevant studies published up to April 19, 2019. The keywords used in the search were fuzzy logic, artificial intelligence, HM and biomechanics. The search was for original articles only. Articles were excluded where the subject contained content review, lesion, disease, treatment, or rehabilitation. Because of the number of articles retrieved through keywords and, the fact that the search strategy did not specify the type of HM, studies related to the physical abilities and motor abilities of healthy individuals were chosen after the screening stage of the articles following the flow chart in Table 1. The systematization PRISMA proposed by Moher et al. (2010) was used.

The articles selected from database searches were subsequently evaluated based on inclusion and exclusion criteria. The inclusion and exclusion criteria are given in Table 2.

The inclusion and exclusion criteria were applied in two screening stages. In the first screening stage, the authors evaluated the content using the title and abstract, and eliminated articles that did not meet the eligibility criteria. The articles that raised doubts about whether these criteria were met proceeded to the second screening stage. In the second screening stage, the articles were read in their entirety and those that did not meet the eligibility criteria were excluded.

A total of nine parameters were extracted from the six articles selected in this systematic review: author, year of publication, motor gesture studied, input (data acquisition), intervention, sample characteristics, applicability, reason for choosing FL, and details of the FL adopted.

Because of the heterogeneity of the protocols found in the selected articles, it was not possible to perform meta-analysis in this study. Thus, the results were analyzed using descriptive statistics; specifically, for each parameter evaluated, an average was calculated that was reported.

4 Results

Figure 1 shows the 951 articles found in PubMed, Scopus, ScienceDirect, and IEEE Xplore. After the removal of 12 duplicates, there were 939 articles. After applying the inclusion and exclusion criteria, and evaluating the title and abstract, 27 articles were obtained. These were read in full and evaluated according to the inclusion and exclusion criteria, which obtained a final number of six articles, which were used in this systematic review.

The characteristics of the selected studies are presented in Table 3. The oldest article was published in 2011 and the most recent was published in 2018.

LF as a tool for AI can be used in various ways, and its main characteristics are described in Table 4.

Table 5 shows that only one article presented the mean and standard deviation of the experimental protocol, whereas the others presented the error rate or false positive level in the protocol.

Table 6 shows a description of the reason for using the FL that was described in each article.

To evaluate the use of FL in the selected studies, the authors verified that the most used motor gesture was gait, which was presented in two studies (33.3%) (Kutilek et al. 2013; Ng et al. 2014), and was the only motor gesture repeated in the selected studies; the motor

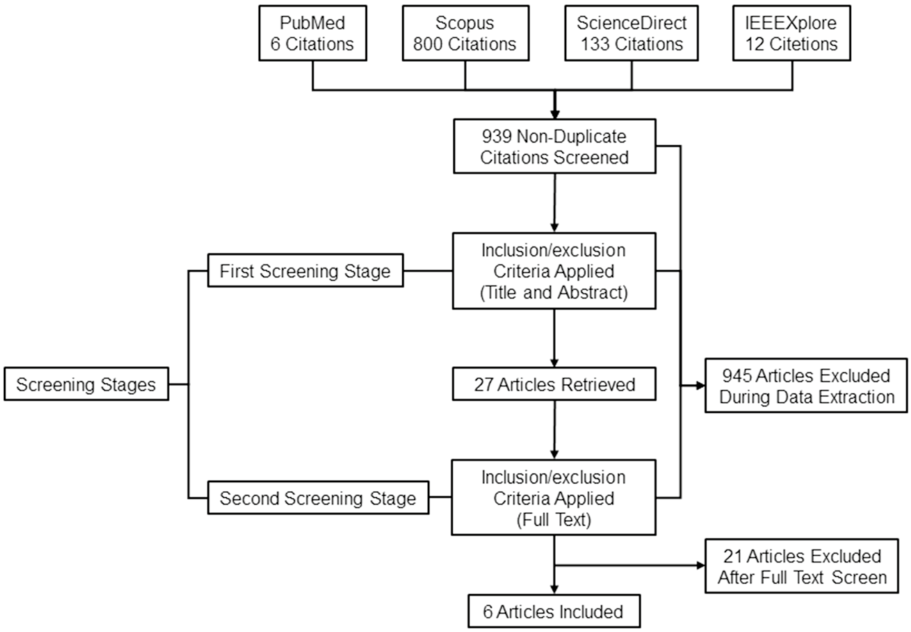

Fig. 1 PRISMA flow chart: screening and selection process

Table 3 Characteristics of selected studies

References	Studied motor gesture	Input (data acquisition)	Intervention and local	Sample	Result	Applicability
Ahamed et al. (2017)	Running	A 3D accelerometer (Shimmer3 GSR + ® ± 8 g, Shimmer Inc., Dublin IE) was placed on the sacrum of each aisle to record the mass acceleration center at a sampling frequency of 201.03 Hz	3 running tests on a treadmill for approximately 60″	3 runners	Accuracy of 96.54%	Yes
Gopalai and Arosha Senanayake (2011)	Wobble Board Training	MicroStrain Inertial Sensors which are triaxial accelerometers, gyroscopes and an on-board processor with triaxial sensor fusion algorithms that support 360º measurement of orientation range across all axes	3 attempts in each condition, totaling 12. Conditions: Eyes open and eyes closed; without vibro-vibratory feedback and with vibrating feedback	6 men and 6 women; age 23.45 (± 1.45) years, BMI 21.85 (± 1.87) kg/m^2	All subjects registered significant improvements (p values of $p < 0.05$)	Not
Kutilek et al. (2013)	Gait	Lukotronic AS200 three-dimensional motion capture system mounted in front or behind the moving object on the treadmill, recording 3D movements of the lower limbs, although only the sagittal plane is being collected	Gait on the Treadmill, varying the speed and incline according to a randomized schedule	10 students	Inference based on an evaluation of the proposed cycle could be sufficiently accurate and adequate if we need to know the approximate type of walking and the approximate angle of inclination of the surface	Not

Table 3 (continued)

References	Studied motor gesture	Input (data acquisition)	Intervention and local	Sample	Result	Applicability
Mebarkia et al. (2014)	To perform three times voluntary isometric contraction at a low strength level	Electromyography (EMG) signs of three muscles (right side): The short abductor of the thumb, the dorsal and the muscles of the biceps brachii	Detection of active motor units performed by an algorithm based on preliminary rules that investigates the three-phase model in the signal. Signals lasting for 10 s were recorded from the three muscles using the bidimensional configuration of 16 electrodes in each attempt of isometric voluntary contraction of low force level	6 women (age: 27.4 ± 3.64 years, height: 1.65 ± 0.08 m, body mass: 74.16 ± 22.85 kg) and 5 man (age: 29.6 ± 4.5 years, height: 1.83 ± 0.07 m, body weight: 85 ± 15.8 kg)	Accuracy of 97.80%	Not

Table 3 (continued)

References	Studied motor gesture	Input (data acquisition)	Intervention and local	Sample	Result	Applicability
Ng et al. (2014)	Gait	Two Sony HDR-XR160E HDR camcorders. The videos were recorded in the MPEG Transport Stream (MTS) format with 1920 resolution (Height) × 1080 (Width) pixels. The video stream was captured using progressive scanning at a frame rate of 50 frames per second (fps). Camcorders captured the walking sequence from two different viewing angles: lateral view and oblique view of 60°	The registration of the MMUGait database was done in an internal environment with a green background and a solid white surface. The subjects walked back and forth on a track continuously and captured in both directions	82 subjects	Accuracy above 90%	Not
Nowshiravan Rahatabad et al. (2012)	Elbow Movements Based on Biceps and Triceps Only	elbow electrogoniometry and EMG were recorded from the muscles and joint, the angles were converted for the moment, by inverse dynamic analysis through MATLAB software (MathWorks, 2005)	A table set to hold the shoulder maintain an angle of 90°. Move the elbow where the hand follows a specific path forward and backward at a distance of 50 cm	3 male subjects aged 21–27, right-handed and without neuromuscular problems	12.4% RMS error (in the worst case) compared to the experiment data	Not

Table 4 Details of the LF adopted in the selected articles

References	Linguistic variables				Details of LF method					
					Membership function	Fuzzy operator	Fuzzy inference	Number of rules	Defuzzification method	Software
Ahamed et al. (2017)	Slow, medium, fast				Triangular	if–then	Mamdani	3	Centroid	MatLab
Gopalai and Arosha Senanayake (2011)	Input		Output		Triangular and trapezoidal	Max–min/ if–then	Mamdani	15	Centroid	LabVIEW 8.5
	Membership functions for trunk measurements (input)	Membership functions for wobble board measurements (input)	Membership function for postural stability							
	Poor, average, good	Negative poor, negative average, good, average, poor	Negative high, negative low, dead zone, low, high							
Kutilek et al. (2013)	Input		Output		Triangular and trapezoidal	If–then	Mamdani	–	–	MatLab
	Small, medium, large	Small negative, small positive, medium positive, large positive	Slow, comfortable, fast	Small, medium, large (stairs)						
Mebarkia et al. (2014)	Small, medium, large				Trapezoidal	If–then	–	10	–	MatLab

Table 4 (continued)

References	Linguistic variables	Details of LF method					
		Membership function	Fuzzy operator	Fuzzy inference	Number of rules	Defuzzification method	Software
Ng et al. (2014)	Euclidean distance metrics with various tests involving approximate values	Using Experiments to Find the Right Rank Rate	and	–	–	–	–
Nowshiravan Rahatabad et al. (2012)	Passive-length force, active-length force and active-speed force of the Hill muscle model and Fuzzy Genetic Implementation Hill-based muscle model	Gaussian fuzzy membership function for input/output sets	and	Zajac	–	–	MatLab

Table 5 Mean and standard deviation, error rate, or false positive rate

References	Mean and standard deviation, error rate or false positive rate	
Ahamed et al. (2017)	Coefficient of determination between actual and predicted values	81%
	Residual standard deviation	0.178
	Mean squared error	0.059
	average absolute error	0.213
	non-dimensional error rate	0.147
Gopalai and Arosha Senanayake (2011)	IMUs Euler Angle Measurements	4.79 ± 1.06 ms
Kutilek et al. (2013)	The slight variability in the estimation of the type of terrain and walking speed may be insignificant, since there are slight variations, even in the human gait	The small differences in the inferred characteristics are comparable to those seen during the measured human natural gait.
Mebarkia et al. (2014)	The total number of motor units with activation potential was classified as a total error	4.97%
Ng et al. (2014)	The system achieved low false positive rates	They are in the range of 0.1–2.6%
Nowshiravan Rahatabad et al. (2012)	Mean square error	less than 5.5656 N

Table 6 Reasons for choosing FL

References	Reason for choosing FL, according to own author
Ahamed et al. (2017)	The FL is an influential rule-based AI technique that helps predict and identify patterns of human gait movement and running conditions identified in previous studies
Gopalai and Arosha Senanayake (2011)	The fuzzy inference system is usually more efficient to determine the level of feedback in the presence of noise as it occurs in appropriate vibro-intervention protocols
Kutilek et al. (2013)	To amplify the studies about FL in the identification of the type of movement of the lower limbs or the type of gait
Mebarkia et al. (2014)	Attempt to better represent the rules generated by the human expert
Ng et al. (2014)	Better understand the Euclidean distance metrics and Linear Discriminant Analysis classifiers requested in the study
Nowshiravan Rahatabad et al. (2012)	O'Brien developed a diffuse muscle model to improve the limitations of the Hill model. He used the fuzzy theory to model the input/output of muscle

gesture of running was used in one study (16.6%) (Ahamed et al. 2017); motor movement control based on the bicep and triceps muscles in flexion and extension with a linear predefined movement of 50 cm was used in one article (16.6%) (Nowshiravan Rahatabad et al. 2012); the balance control motor gesture on a wobble board was used in one article (16.6%) (Gopalai and Arosha Senanayake 2011); and the motor control gesture of the abductor short of the thumb, dorsal muscles, and muscles of the biceps brachii in voluntary isometric contraction at a low level of strength was used in one article (16.6%) (Mebarkia et al. 2014).

Data acquisition in the selected articles was performed by the equipment used to analyze the HM of healthy people, which had the characteristics of the ability to collect data and report directly using language that could be processed by a computer. EMG was used in two studies (33.3%) (Mebarkia et al. 2014; Nowshiravan Rahatabad et al. 2012), where one study simultaneously used an electrogoniometer (16.6%) (Nowshiravan Rahatabad et al. 2012); in two studies, triaxial accelerometers (33.3%) were used; and in two studies, three-dimensional (3D) kinematic analyses (33.3%) (Kutilek et al. 2013; Ng et al. 2014) were performed using two specifically positioned cameras.

All the selected articles had protocols for which AI using FL presented statistically satisfactory results, thereby demonstrating that AI using FL, with its peculiarities, can be considered a reliable tool for the analysis of HM within the presented procedure.

The only article that presented a method with applicability within the free-living model was that of Ahamed et al. (2017), which used an accelerometer to generate input (data acquisition).

5 Discussion

The present review brought together articles that involve the results of studies that used AI and FL applied solely to assess the voluntary HM of healthy people. There is no preferred data acquisition mechanism for studying HM, and simpler mechanisms appear to have better applicability. The selected studies evaluated the applicability of FL by analyzing different types of locomotor movement and, overall, they presented statistically satisfactory results.

The present work corroborates the systematic review study developed by Cust et al. (2019) with respect to results that involve using AI to evaluate HM. The studies have methodological differences because the present study involved a search for articles on the FL tool used for healthy people, whereas the study by Cust et al. (2019) did not specify a tool for AI and sought to identify sporting gestures.

Regarding sports, only one out of the six articles evaluated the locomotor gesture of running, but without the objective of identifying performance. In the article by Ahamed et al. (2017), LF inferences were used to generate qualitative running velocity responses to characterize slow, medium, and fast. Other ways of using this mechanism, based on a triaxial accelerometer, could be explored to improve sports performance by correlating qualitative data with training levels and categories.

Half of the selected studies were directed to understanding human locomotion: two involved gait (33.3%) (Kutilek et al. 2013; Ng et al. 2014) and one involved running (16.6%) (Ahamed et al. 2017). The low number of articles that involved the subject FL and healthy people demonstrates that we may be taking the first steps toward automating the HM analysis of healthy people.

Kutilek et al. (2013) used cyclograms, which were designed by collecting human gait patterns that characterize the speed of travel and the slope of the terrain. The data collected for the formation of cyclogram patterns fed databases that could be used later in the development of new studies and new technologies that may require this identification.

The study by Kutilek et al. (2013) sought to deepen a nebulous and specialized method of data collection with the purpose of presenting a basis to be applied in the possible development of robotic prostheses or locomotion therapies. For purposes other than Ng et al. (2014) proposed a more robust method for understanding the data collected. In the selected studies, 3D kinematic analysis was used the proposed input (data acquisition) to understanding data regarding the development of a specific motion because it could represent a large amount of data.

Because FL is linked to correlations, feeding the database to minimize possible errors is a task that can be continuously updated. The study developed by Ng et al. (2014) is an example of how the system can be fed to reduce errors because this case included the addition of people using a series of objects that obstructed the reading of data, but the accuracy of the reading remained high, even if it considered more than one individual at a time. This system could contribute to making it more possible to identify data for people in a free-living context performing their daily tasks.

Although the study by Ahamed et al. (2017) succeeded in identifying a highly accurate method of analysis, it is evident that to improve the understanding of running, it would be necessary to implement a larger number of corridors and more sensors, such as GPS. Following a different path, Kutilek et al. (2013) and Ng et al. (2014), used AI and FL in the kinematic reading to collect gait data that could be applicable to other studies, which demonstrated an interest in presenting only findings without intervention through the proposed method. Other studies using AI through ANNs have validated, with important results, the use of accelerometers to estimate caloric expenditure during physical activity, thereby demonstrating that there is a huge depth of studies possible in this path (Montoye et al. 2016).

The only study found on AI using FL for balance control analysis was developed by Gopalai and Arosha Senanayake (2011), who used a protocol on an unstable platform (wobble board) with closed eyes and open eyes, and with and without vibratory feedback.

The study aimed at determining the characteristics of the conditions proposed in the experiment.

The feedback system presented by Gopalai and Arosha Senanayake (2011), based on vibrotactile sensors, which warn of possible inadequate postural controls, is presented as an alternative to the development of acute physical capacity improvements. Although it may represent a wide range of possible developments, the study focused on the postural control of healthy people, thereby demonstrating findings on the behavior of HM.

Accelerometer-based data acquisition (input) used in the selected articles searched data that referred to the repetition of an event, such as that which occurs in the course of running or the oscillation of equilibrium control.

Mebarkia et al. (2014) proposed recognizing the motor units (MUs) that are activated (action potential [MUAP]) through AI using FL, and developed a tool that is capable of performing such a function.

The recognition of MUAPS in healthy people was also a finding, but in this case, the improvement was caused by the use of AI in the proposed model through LF. For Mebarkia et al. (2014), the findings contributed to studies that now understand the functioning of muscle tissue more robustly.

Nowshiravan Rahatabad et al. (2012) aimed to present an adequate tool to compare artificial and biological muscle, and used EMG signals as one of its inputs and force as the output. Such a model can assist in the production of efficient artificial muscles that meet the criteria of the biological muscle.

To understand the motor control behavior of biological muscle, Nowshiravan Rahatabad et al. (2012), found that the LF-based AI model proposed in the study is an efficient form of control for artificial muscles that are controlled by the same neuromotor mechanism. Therefore, it is a study that seeks the development of robotics through human modeling.

Selected researchers that have used input (data acquisition) aimed at identifying some muscle control characteristics have chosen to use EMG, as found in Mebarkia et al. (2014) and Nowshiravan Rahatabad et al. (2012).

According to Ma et al. (2017), FL theory involves rough or flexible sets that are essentially mathematical tools that provide calculation mechanisms to manage uncertainties. The selected studies do not disagree with the proposed FL concept and use it to deal with uncertainties. HM is complex and susceptible to uncertainties; thus, FL contributes to the evolution of methods that can deal with this context.

Even though the FL concept was successfully applied in selected articles, the challenge of conducting the implementation of AI in the research environment must be considered to seek increasingly efficient solutions for an evolution of methods and procedures.

The data collections presented in the selected articles demonstrated structural problems, which necessitated adaptations in their procedures, which mostly reduced variables for simpler protocols and generated simpler data. It is worth mentioning that 83.3% of the selected studies do not have applicability within the free-living model because of difficulties in data acquisition outside a laboratory environment.

No AI studies were found that use FL in the evaluation of the HM of healthy people that were directed to the understanding of the performance of some physical or sports capacity. It is hoped that as data inputs for new technologies evolve, new possibilities may arise for actual application.

6 Conclusion

AI using FL, according to the selected studies, presents statistically satisfactory results because of the low error rates or production of data considered to be false in the evaluation of the HM of healthy people. The literature presents a few recent studies on the subject. Even with the advantages of the model, there are still limitations to the use of this technology because of the difficulty of implementation in the free-living context, that is, the collection environments are still very controlled in laboratories. Even in this context, devices have been studied that can be applicability within the free-living model context. Multiple devices can be used for data generation through FL-based AI responses. The selected studies presented a nonhomogeneous variety of devices and motor gestures in their protocols, despite half of the studies being involved in human locomotion. The selected studies did not seek to characterize human performance or more vigorous gestures. The main reason for using FL as an AI tool was linked to the simplicity context of the correlation-based model for dealing with data collection or responses that may be "inaccurate."

Acknowledgements We offer special thanks to the members of the Occupational Biomechanics and Quality of Life Research Center (Nucleo de Pesquisa em Biomecânica Ocupacional e Qualidade de Vida - NPBOQV). We thank Maxine Garcia, PhD, from Edanz Group (www.edanzediting.com/ac) for editing a draft of this manuscript.

Author contributions BL together with the advisor GV defined the theme of the paper. BL performed the search on the Scopus, PubMed, IEEEXplore, and ScienceDirect databases and withdrew duplicate articles. The inclusion and exclusion criteria for the title and abstract were applied by BL, CN, CF, FV, and LB, and then compared and debated. The inclusion and exclusion criteria for the full text were applied by BL, RP, and PB, and then compared and debated. The text was written by BL and revised by RP, PB, CN, FC, FV, LB, and GV in meetings coordinated by GV. The translation was performed by BL, PB, and GV.

Funding There was no external funding for this project.

Availability of data and materials The data supporting the conclusions of this article are included in the article itself.

Compliance with ethical standards

Conflict of interest We declare no conflict of interest.

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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