Multibody Kinematics Optimization for the Estimation of Upper and Lower Limb Human Joint Kinematics: A Systematized Methodological Review

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http://dx.doi.org/10.1115/1.4038741

Journal of Biomechanical Engineering

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ABSTRACT

Multibody kinematics optimization (MKO) aims to reduce soft tissue artefact (STA) and is a key step in musculoskeletal modeling. The objective of this review was to identify the numerical methods, their validation and performance for the estimation of the human joint kinematics using MKO.

Seventy-four articles were extracted from a systematized search in five databases and cross-referencing. Model-derived kinematics were obtained using either optimization or Kalman filtering to minimize the difference between measured (*i.e.*, by skin markers, electromagnetic or inertial sensors) and model-derived positions and/or orientations. While hinge, universal and spherical joints prevail, advanced models (*e.g.*, parallel and four-bar mechanisms, elastic joint) have been introduced, mainly for the knee and shoulder joints. Models and methods were evaluated using: (i) simulated data based, however, on oversimplified STA and joint models; (ii) reconstruction residual errors, ranging from 4 mm to 40 mm; (iii) sensitivity analyses which highlighted the effect (up to 36° and 12 mm) of model geometrical parameters, joint models, and computational methods; (iv) comparison with other approaches (*i.e.*, single body optimization and non-optimized kinematics); (v) repeatability studies that showed low intra- and inter-observer variability; and (vi) validation against ground-truth bone kinematics (with errors between 1° and 22° for tibiofemoral rotations and between 3° and 10° for glenohumeral rotations). Moreover, MKO was applied to various movements (*e.g.*, walking, running, arm elevation).

Additional validations, especially for the upper-limb, should be undertaken and we recommend a more systematic approach for the evaluation of MKO. In addition, further model development, scaling and personalization methods are required to better estimate the secondary degrees-of-freedom.

KEYWORDS

Kinematic chain, joint model, skin markers, optimization, Kalman filter, validation, state-of-the-art

1. INTRODUCTION

There is a growing use of multibody kinematics optimization (MKO) to estimate human joint kinematics from stereophotogrammetry or other motion analysis systems, such as electromagnetic sensors or inertial sensors. While innovative approaches are emerging (*e.g.* markerless, sensorless or single camera) for motion analysis, they are not commonly used in biomechanics because their accuracy in in-situ complex movements has not yet been well established [1]. MKO is a key step in musculoskeletal modeling, but it is also used in kinematic and dynamic analyses of human movement with the aim of compensating for soft tissue artefact (STA).

Referred to as 'global optimization', 'multibody optimization', 'inverse kinematics' or 'motion reconstruction' according to the field of research, the method is referred to as

MKO in the present study. This diversity of both terminology and research fields may explain the lack of reviews on this topic. Note that two overviews – although not systematic nor systematized – have recently been published regarding kinematic models of the upper [2] and lower [3] limb used in MKO. MKO simultaneously determines the pose of all segments while enforcing the constraints imposed by various joints in a unique optimization process. By contrast, other kinematics optimization methods (*e.g.*, singular value decomposition method [4], solidification procedure [5], point cluster technique [6], optimal common shape technique [7]) consider each segment independently. They are referred to as single-body kinematics optimization (SKO). MKO requires a model of the osteo-articular system as a kinematic chain, *i.e.* a series of rigid segments connected by joints, allowing a specific number of degrees-of-freedom (DoFs) to the model. Several joint mechanisms have been developed [2, 3] and combined in MKO models. An exhaustive list with their rationale, performance and numerical implementation may help orient the future developments.

The main principle of MKO is to minimize the difference between measured and model-derived skin-marker trajectories (or sensor orientations and positions, velocities *etc.*) which are subject to some rigid body and kinematic constraints. However, several numerical methods can fulfill this one principle. Their relevance depends on the design variables (i.e., inputs of the optimization problem), objective function, constraints, resolution algorithm, initial guess, *etc.* Typically, both constrained optimization and Kalman filters have equivalently been implemented as MKO. Kalman filters apply a two-stage predictor-corrector procedure in which the system and measurement models are used to predict the expected progression of the system states, output and error covariance matrix, which are subsequently corrected by the measurement.

The model-derived kinematics largely depend on the modelling choices and joint kinematics accuracy is not well established. The purpose of this systematized review was to identify the numerical methods and evaluate their performance to estimate human upper and lower limb joint kinematics using MKO from commonly used systems (active/passive makers, electromagnetic and inertial sensors). A secondary objective was to identify the different fields of application of MKO.

2. METHODS

2.1. Search strategy

An electronic search was performed in October 2016 in Embase, Medline, PubMed, Scopus, and Web of Knowledge. Logical expressions for the search included 'optim* or kalman', 'kinemat* or joint', 'subject or human', and 'model* or over*determ*'. The search was performed on the title, keywords and abstract. The reference lists of key studies were also cross-referenced (*i.e.*, articles either cited in or citing these studies) to obtain further articles. All years of publication were considered.

2.2. Inclusion and exclusion criteria

Articles retrieved from the search strategy were appraised by one author according to the following inclusion- exclusion criteria. Only studies in English that reported kinematic results were included. Studies published as conference proceedings, studies concerning single body or under-constrained optimization, estimation of joint centers or axes, predictive simulation, studies presenting methods whose outcome is not joint or segment angles, studies performing markerless, sensorless or single-camera motion analysis, studies on cadaveric specimens, animals, robots or machines, studies focusing solely on finger, foot, or spine were omitted.

2.3. Quality assessment

A customized checklist of 15 questions was developed based on previous reviews in the field of biomechanics [8-10] to assess the quality of the methods proposed by the studies included in the present review (Appendix, Table S1). Each question was rated zero (no information), one (limited details) or two (satisfying description or justification) or indicated non-applicable (this applies only to questions Q5, Q6, Q7, Q8 and Q10 about experimental setup, evaluation and statistics). Each study was independently evaluated by one of three reviewers (no reviewer evaluated articles he co-authored). Conformity was previously obtained using a sample of 20 articles evaluated by all three authors followed by a discussion to understand and mitigate the difference.

2.4. Information extraction

To answer the two aforementioned questions (what are the numerical methods? and what is the type of validation of the MKO?), the following themes were listed and each was addressed by one reviewer: design variables and objective function, constraints and model geometric parameters, resolution algorithm and initial guess, evaluation strategy, reference data, and degree of agreement. In order to meet the secondary objective, an additional theme was the field the application of the MKO.

3. RESULTS

3.1. Search yield

The search results were in Embase: 865 articles, Medline: 803, PubMed: 187, Scopus: 940, Web of Knowledge: 688. After removing duplicates, the number of articles was 1577. After applying the exclusion criteria, 52 articles were selected for the review and 22 additional articles were obtained by cross-referencing. With all our attempts of logical expressions of keywords, the variety of expressions used in the literature for describing the "multibody kinematics optimization" made the search incomplete without cross-referencing.

3.2. Quality assessment

The scores of quality ranged from 13 (43.3%) to 30 (100%), with a mean score of 23 (76.7%). N/A was occasionally indicated for questions Q5, Q6, Q7, Q8 and Q10 for studies not performing any evaluation, evaluating MKO on simulated data only (*i.e.*, no participants involved), or that did not perform statistical analyses. A score of 0 was indicated in 22 articles for the question Q13 about the quality of the stated limitations. Substantial variability was reported in writing style and article structure between journals dealing with different fields such as biomechanics, robotics, ergonomics, computer animation, *etc*. The relevant information may, therefore, sometimes be difficult to retrieve and subject to the reviewer interpretation.

3.3. Numerical methods

Two categories of methods were found in the included studies, namely constrained optimization and Kalman filters. In this review, we consider unconstrained optimization as a special case of constrained optimization. For sake of clarity and comparison between the two categories, the references for the design variables and the constraints of the optimization are grouped in Tables 1 and 2.

3.3.1. Constrained optimization

As stated in the introduction, the main principle of MKO is to minimize the difference between measured and model-derived skin-marker trajectories (or sensor orientations and position, velocities, *etc.*). The next subsections describe the design variables, the objective function, the constraints and initial guess of the optimization problem used in MKO.

3.3.1.1 Design variables

In most cases, the design variables optimized by MKO are joint angles (Table 1). As when using Kalman filters (see section 3.3.2), the number of joint angles and the number of DoFs are the same (*i.e.*, generalized coordinates) and no rigid body or kinematic constraints are required except in the case of additional closed loops [11-13].

Nevertheless, quaternions and rotations matrices were also proposed for numerical convenience as well as natural coordinates (*i.e.*, Cartesian coordinates of points and components of axes describing the segments). The design variables can also include the model's geometric parameters (*i.e.*, segment lengths, position of joint centers and orientation of joint axes, position of markers embedded in the segments).

Table 1: Design variables of the MKO problems

Variables	**Occurrence**	**Constrained optimization**	**Kalman filter**
Generalized coordinates	20 + 6	[12-32]	[11, 18, 33-38]
Velocities	2 + 6	[32, 39]	[11, 33-38]
Accelerations	2 + 6	[32, 39]	[11 , 33-37]
Jerk	1		[40]
Rotation matrices	9 + 1	[41-49]	[37]
Natural coordinates	8	[50-57]	
Quaternions	5	[32, 58-61]	[37]
Model parameters	4 + 3	[14, 62]* [16, 22]†	[33-35]

* within a large-scale optimization (one vector that concatenates time-varying coordinates at all sampled instants of time and constant model parameters)
† two-level optimization

3.3.1.2 Objective function

Unless inertial [59] and magnetic [21] sensors are used, the objective function used in all studies is the sum of the squared distances between measured and model-derived skin-marker positions. One study replaced the measured skin-marker by virtual markers representing the segment coordinate systems obtained by a SKO [31]. In many studies, some marker weights are introduced in the objective function [14, 23, 29-32, 41-

43, 45, 48, 50, 61]. The weights are generally defined according to the marker residuals resulting from a first optimization performed without weights or based on reported amount of STA. In two studies [29, 31], marker weights were chosen so that every segment had an equal weighting. Another rationale for the estimation of marker weights was introduced by [27], considering the projection of the markers onto a selected axis to cancel the marker (and corresponding STA) effect on this DoF.

Alternative objective functions include the sum of the squared errors between measured (*i.e.*, computed from skin markers without optimization) and model-derived joint angles [12, 63], the sum of the squared errors between measured (*i.e.*, obtained from inertial sensors) and model-derived attitude vectors [59], or the weighted sum of the squared errors between measured (*i.e.*, obtained from magnetic sensors) and model-derived positions and attitude vectors [21].

Some penalty terms were also appended to the objective function in order to consider 'soft' kinematic constraints, especially for defining deformable ligaments [12, 51, 54, 56] or an elastic joint [43, 57]. A unique study also introduced the sum of the length variations of the musculo-tendon elements as a penalty term [14]. Another study penalizes the knee adduction-abduction [16]. Generally speaking, all terms of the objective function can be considered as 'soft' constraints, *i.e.* the skin-marker positions (or sensors orientation) defining a set of so-called driving constraints to be minimized [24, 50, 56, 61].

3.3.1.3 Constraints

According to the choice of the design variables, in case they are not independent of one another, some rigid body constraints must be considered such as the norm of the quaternions, the orthogonally of the rotation matrix, and the constant distances and angles between points and axes describing the rigid segments in case of natural coordinates (Table 2). When the design variables are joint angles, their choice implicitly defines the DoFs of kinematic chain in accordance with the Denavit-Hartemberg convention or Euler/Cardan angles. This means that the joint models are typically defined as spherical, universal or hinge. In this case, the joint angles are sometimes bounded in a physiological range. Otherwise, the kinematic constraints must be defined explicitly as it is specifically done for complex joint models such as parallel or four-bar mechanisms. These kinds of joint models typically include constant length of various ligaments. Other kinematic constraints for complex joints include sphere-on-plane, sphere-on-sphere and point-on-ellipsoid contacts. These kinematic constraints for ligaments and articular contacts are used to model the shoulder, knee and ankle joints. Another possibility is to prescribe coupling equations between the DoFs. Additional kinematic constraints can represent closed loops not within the kinematic chain itself, but with accessories like paddles or footrests [11]. All the aforementioned kinematic constraints stand for 'hard' (deterministic) constraints. As previously explained, the definition of 'soft' constraints relies on the introduction of penalty terms in the objective function. This was typically proposed for some ligaments [12, 51, 54, 56], some scapulothoraric and glenohumeral articular contacts [12, 43] and closed loops with the environment [11].

The absence of kinematic constraints was implemented as a marginal case of MKO equivalent to a SKO. When the model geometrical parameters are part of the design variables, in the same way as the joint angles, they are sometimes constrained and/or bounded within a physiological range.

Table 2: Constraints in the MKO problems

Constraints			**Occurrence**	**Constrained optimization**	**Kalman filter**
Hard constraints	Joint	Spherical, universal or hinge	26 + 5†	[13, 14, 16-19, 21-23, 25-27, 32, 48, 49, 58, 60, 62, 64-71]	[11, 18, 33, 35, 36, 40]
			7‡	[18, 42, 43, 46, 47, 58, 61]	
		Parallel or 4-bar mechanisms	5	[52, 53, 55, 70, 72]	
		Sphere-on-plane	6	[51, 52, 54-56, 72]	
		Sphere-on-sphere	1	[53]	
		Point-on-ellipsoid	3	[12, 20, 53]	
	Rigid body	Norm of quaternion	2	[32, 61]	
		Matrix orthogonality	1	[45]	
		Segment distances/angles*	2	[50, 52]	
	Ligament	Conoid	2	[12, 20]	
		Cruciate	7	[51, 52, 54-56, 70, 72]	
		Collateral	6	[51, 52, 54-56, 72]	
		Patellar	1	[72]	
		Tibiocalcaneal and calcaneofibular	3	[52, 70, 72]	
Soft constraints (in the objective function)		Norm of quaternion	1		[37]
		Ligament length	4	[12, 51, 54, 56]	
		Elastic joint	2+1	[43, 57]	[37]§
		Musculo-tendon length	1	[14]	
		Knee abduction	1	[16]	
		Closed-loop with accessories	1	[11]	[11]
Bounds		Joint range	4	[11, 19, 26, 73]	
		Model parameters	2	[16, 62]	
Equations	Joint	Coupling motion	12 + 1	Knee [40, 65, 74-80]; Ankle [65, 74, 79]	Knee [40]
No constraints			5	[51, 52, 54, 75, 81]	

† implicit constraints defined through generalized coordinates
‡ explicit constraints (*e.g.* combined with natural coordinates)
* in case of natural coordinates
§ spherical joint with penalties on the translation
Note: some references can be cited in different categories since the model includes several joints and authors may have implemented different models.

3.3.1.4 Initial guess and model geometric parameters

The definition of the initial guess of the optimization process is rarely detailed in the reviewed studies, particularly when the design variables are the joint angles. Nevertheless, the solution for each sampled instant of time can be used as the initial guess for the next one [25]. In MKO based on quaternions or rotation matrices, the initial guess at each sampled instant of time is often defined as the kinematics resulting from SKO applied to the skin markers [44, 58]. MKO based on natural coordinates reported an initial guess of the points and axes describing the segments similarly obtained from the skin marker positions at each sampled instant of time [52, 56, 72]. As these natural coordinates enclose additional information about the segment geometry, the definition of the model geometrical parameters is also commonly derived from this initial guess by averaging segment lengths, position and orientations of joint centers and axis over all the sampled instants of time. Alternatively [11, 13, 15, 17, 23, 24, 27, 31, 47, 48, 63], optimal joint centers and axes can be defined using functional methods (*e.g.*, SARA and SCoRE algorithms [82, 83]) from dedicated movements. When segment geometry is part of the design variables [14, 16, 22, 62], the geometry is optimized for the movement of interest. Nevertheless, most of the model geometrical parameters are generally defined using the skin marker positions put on bony landmarks in a static posture [23, 41, 42, 47, 49, 69]. Interestingly, one study compared two static postures and demonstrated that the model-derived kinematics is highly affected by the chosen posture [49]. It is, however, in a static posture that generic models are generally scaled to fit the subject anthropometry. Scaling is usually based on segment dimensions [28-31, 39, 84] but more complex transformations (*i.e.*, affine or interpolations) based on skin marker positions can also be used [12, 53, 60]. Other scaling strategies rely on geometric fitting of some skin marker positions in multiple static postures [20]. Finally, scaled, generic models are increasingly replaced by subject-specific models. Most of the time, the personalized bone and joint geometries are obtained from magnetic resonance imaging [43, 70, 75, 78, 85], computed tomography [66, 67, 80] or bi-plane radiography [51]. Personalization of the coupling equations between the knee DoFs [80] and personalization of the patellar ligament length [66] were also implemented using fluoroscopy data.

3.3.2. Kalman filters

As in constrained optimization, Kalman filtering has also been applied for movement reconstruction. The original Kalman filter [86] was developed for optimal estimation of the system state for linear dynamical systems subject to zero-mean, Gaussian process and measurement noises. Advanced Kalman filter approaches have subsequently been developed to cope with nonlinear systems [87], such as extended and unscented Kalman filters as well as Kalman smoothing, which is an offline estimation approach, where the measurements are filtered both forward and backwards in time.

3.3.2.1 State variables

In all reviewed papers except [37], the state variables contain the generalized joint coordinates with their number matching the number of DoFs of the system and a specified number of time derivatives, typically up to accelerations, but there are also studies which include up to the velocities or up to jerk (Table 1). Additionally, Cerveri et al. [34] introduced the local coordinates of markers and joint centers (and their derivatives) in the state variables to enable their online estimations. When the measurements come from inertial sensors and not 2D or 3D markers, state variables were expressed in different ways. Miezal et al. [37] included the translations and orientation of the inertial sensors, their linear and angular velocities and linear accelerations in the state vector. Alternatively, they included the translation and orientation of the segments plus the angular accelerations in the state vector.

3.3.2.2 System models

The system model (or process model) is constructed from a Taylor series expansion such that the highest order derivatives included in the state variables are considered constant. The noise on the system model is modelled as a zero-mean, Gaussian process noise with a specified covariance. Cerveri et al. [35] described how this can be determined as a function of the dynamic content of the system variables, if known. Alternatively, it can be updated online [33].

3.3.2.3 Measurement models

Depending on the measurements available, different measurement models have been developed. When skin marker trajectories are measured, the measurement model expresses the relationship between the state variables and the measured marker coordinates, which can either be in the 2D camera image reference frame [33-35] or the 3D laboratory reference frame [40]. As a part of the measurement model, the geometry of the assumed underlying model must be included. This involves the determination of the joint centers and local marker coordinates in technical reference frames. Cerveri et al. [33-35] accomplished this using a standing reference trial and anthropometric measurements, as it is typically accomplished in clinical marker-based analyses. Besides a reference trial, Jackson et al. [18] performed functional trials from which joint centers were determined. Contrary, De Groote et al. [40] used a cadaver-based musculoskeletal model as the template and scaled it linearly to the dimensions of the subject and hereby differences in joint alignment between the subject and the cadaver were not accounted for. In the cases where inertial sensors are used [38] to measure the movements, the measurement model relates the state variables to the measurements from the available sensors such as gyroscopes, accelerometers, magnetometers *etc*. The measurement model can also be used to enforce constraints which are required for the formulations that do not use generalized joint coordinates in the state vector [37] or which include closed-loop [11]. This is the typical way to implement penalty-based methods (*i.e.*, 'soft' constraints) in Kalman filters.

The measurement noise is modelled as a zero-mean, Gaussian noise with an assumed covariance and is used to specify how confident the user is in the filter prediction compared to the measurements. Choices for the parameters are included in some of the reviewed papers [33-36], but the sensitivity of the predictions to these parameters have not yet been reported.

3.3.2.4 Initial condition

In the Kalman filters, an initial values of the state vector and an initial estimate of the state covariance matrix are required. Contrary to the constrained optimization approaches, that require an initial guess of the variables at each instant of time and use these to search for an optimal solution, the initial conditions in the Kalman filter specify the solution at the first frame. Subsequent frames evolve from this frame and ideally converge to the expected state estimates within a short time period. As a result, the estimated time evolution of the state variables depends directly on this initial condition. However, the initial condition was only clearly defined in 4 of the 10 papers involving Kalman filtering [11, 35-37]. In all these, the pose was determined in a starting configuration and all required time derivatives were assumed to be zero. The initial guess of the state covariance matrix was not detailed in any of the reviewed papers.

3.4. Evaluation and validation of the model-derived kinematics

Almost all studies, except four, include an evaluation of the optimized kinematic results. However, the results were evaluated using different strategies. The evaluation strategies include assessments using simulated data, reconstruction error, sensitivity analyses, repeatability studies, comparison between various approaches or algorithms and validation against reference data (Table 3).

Table 3: Types of validation of the MKO. Subcategories are explained in the notes (*,†,‡)

Type of validation		Occurence	Constrained optimization and Kalman filter
Simulated data		8	[22, 33, 37, 40, 44, 45, 48, 50]
Residual error	3D positions	13	[11, 13-16, 21, 24, 32, 35, 47, 50, 61, 64]
	2D positions	2	[33, 35]
Sensitivity analysis	Monte Carlo		[60, 67-69, 72, 77, 85]
	Geometrical parameters*	7	[13, 17, 20, 60, 63]; [78, 80]
	Joint constraints	6	[13, 41, 46, 52, 56, 79]
Comparison	MKO *vs* SKO and no optimization	10	[8, 23, 26, 31, 34, 45, 46, 61, 71, 74]
	Constrained optim. vs Kalman filter	2	[11, 40]
Repeatability	Intra-subject	2	[16, 29]
	Inter-observer	1	[16]
Validation against reference data	Optoelectronic systems†	5	[36-38, 59, 88]
	Palpation	2	[12, 53]
	Bone kinematics‡	12	[27, 39, 54, 81] 50; [43, 49, 57, 66, 76]; [51, 55]
None		4	[19, 25, 42, 73]

Notes: the references are organized as follow:
* regression *versus* functional methods; generic *versus* personalized
† in case of inertial and magnetic measurement units
‡ intracortical pins; dynamic stereo-radiography; and biplanar X-rays

3.4.1 Evaluation using simulated data

Some innovative algorithms for MKO were initially tested using simulated data, often as a proof of concept (*e.g.*, convergence and calculation cost), where noise is added to the reference kinematics. This noise, modelling the STA, was almost always defined as random and continuous components initially proposed by [5]. A summary of noise parameters for the lower limb can be found in [28]. Generally, MKO showed a good ability to cope with this simulated noisy data, highlighting the relevance of innovative algorithms or their superiority over conventional methods (see section 3.4.4).

3.4.2 Reconstruction error

Nearly a quarter of the experimental studies reported the mean residual error on the marker positions. This metric derives from the objective function and was used to compare different models and methods, marker sets or levels of personalization. Similarly, Cerveri et al. [33, 35] also reported the reconstruction error in pixels relative to the marker 2D position in each camera image reference frame. In essence, a large range of residual values were found (4-40 mm) according to the complexity of the kinematic chain model (*e.g.*, upper-limb or full body), the degree of personalization and the movement of interest.

3.4.3 Sensitivity analyses

Most sensitivity analyses focused on uncertainties of continuous variables (*e.g.*, segment length, position of joint center) and used Monte Carlo methods. Different sets of geometrical parameters obtained by regression *versus* functional methods or scaled generic *versus* personalized models were also compared. Additionally, the effect of different joint constraints was widely assessed.

Although each study used different ranges of uncertainty and different metrics, resulting standard deviation in model-derived joint kinematics reached up to 36° and 12 mm [72]. Sensitivity analyses demonstrated that STA had the most deleterious effect on hip gait kinematics [28, 77], while errors in bony landmark location resulted in moderate effects [69, 72, 77, 85]. Moreover, sensitivity of MKO to reduced marker sets [15, 64] showed good performance with less than three markers per body segment. Yet, MKO cannot limit the discrepancy attributed to different marker sets [29].

In terms of model geometry, functionally located centers of rotation for the hip, knee, and ankle gave slightly modified joint angles [63], while functionally determined axes and centers of rotation on the upper-limb resulted in larger pronation-supination range of motion [13, 17]. Prinold and Bull [20] showed that shoulder models without appropriate scaling of the ellipsoid resulted in kinematics spikes during pull-ups.

Joint constraints affect the resulting joint kinematics, especially the secondary (also called combined) DoFs like knee abduction or rotation [41, 46, 52, 79]. Joint constraints also affect the location of the knee lateral and medial contact points [56].

3.4.4 Comparison between approaches or algorithms

Multiple comparative studies were carried out between MKO, SKO and joint kinematics estimated without optimization. Only two studies compared constrained optimization and Kalman filtering. Some features favoring MKO over SKO or non-optimized kinematics were inter and intra-observer repeatability [16], robustness to marker mislocation [71], and avoidance of joint dislocations [45, 61, 79]. Most studies reinforced the conclusion that the effect of joint constraints is more pronounced on the secondary DoFs of gait [23, 46, 74]. Comparisons between constrained optimization and Kalman filtering showed that the benefit of Kalman filtering is not visible on the joint angle time histories but, unsurprisingly, on the velocities and accelerations [11, 40].

3.4.5 Repeatability studies

Only two studies reported the repeatability of the MKO approach [16, 29]. MKO showed a lower intra-subject and inter-observer variability than the commonly used Newington–Helen Hayes gait model for clinically significant output variables (joint angles, forces and moments) [16]. Moreover, using MKO, the inter-trial variability was consistent across different marker sets [29].

3.4.6 Validation against reference data

Only 12 of the 74 studies validated the optimized kinematics against a gold standard, which consists of ground-truth bone kinematics of upper or lower-limbs obtained using either intracortical pins, dynamic stereo-radiography, and biplanar X-rays. Interestingly, the study of Seth et al. [39] is the only one that did not assess the ability of MKO to reduce STA but rather the bio-fidelity of the model, *i.e.* its capacity to replicate errorless skeletal kinematics.

When validated against reference data on asymptomatic subjects, the typical errors for the model-derived tibiofemoral rotations were between 1° and 22° and between 1 mm and 8 mm during squat, stair ascent, gait and running movements and the errors were maximal for internal-external rotation, anterior-posterior and proximal-distal displacements [51, 54, 55, 57, 81]. A detailed outline of the errors for the model-derived tibiofemoral kinematics can be found in [3]. Typical errors for the model-derived glenohumeral rotations were between 3° and 10° during arm flexion and abduction and the errors were maximal for internal-external rotation [27, 43]. Studies have highlighted that detailed (*i.e.*, including ligament constraints) [54, 55] and subject-specific [51, 66] knee joint models are required to accurately estimate the secondary knee DoF kinematics. Indeed, hinge or spherical joint models led to larger errors than non-optimized kinematics or double calibration [49, 81].

In terms of technologies, comparisons were performed between inertial and magnetic measurement units and optoelectronic systems (although not a 'gold standard', authors consider this as the method of reference). For the upper limb, especially for the scapula, two studies compared the model-derived kinematics with manual palpation (again, here, considered as a reference method).

3.5 Fields of application

MKO applications include clinical and sports biomechanics (Table 4). Gait, especially walking in a straight line but also with changes in direction, have been the most studied movements (∼50% of the studies). Other activities of daily living involving the lower extremities like stair descent/ascent, sit-to-stand motion, manual wheelchair transfer, and generic reach and steering movements involving the upper limb were also of interest. Analytical movements of the upper-limb (arm elevation and rotation as well as elbow flexion and pronation-supination) were studied. Studies including analytical movements of the lower-limb were less frequent. Regarding sports biomechanics, several movements were assessed, namely running, jumping, side-cutting maneuvers, squats and, in an isolated manner, pull-up, movements on a slideboard, in gymnastics, fencing, and kayak.

Table 4: Fields of MKO applications. Subcategories are explained in the notes (*,†,‡,§,′,″)

Activities		Occurrence	Constrained optimization and Kalman filter
Daily living activities	Lower-Limb : Walking*	37	[16, 22, 25, 28-31, 33, 35, 38, 40-42, 45-47, 52, 56, 59-62, 67-72, 74, 75, 77-81, 85, 88]; [66]
	Lower-Limb: others†	7	[46, 49, 57, 58, 70]; [49, 70]
	Upper-limb‡	4	[64]; [35, 50]; [50]
Analytical movements	Lower-limb	4	[22, 34, 49, 62]
	Upper limb§	14	[12, 18, 20, 21, 27, 43, 48, 53]; [13, 17, 19, 36, 48, 73]
Sports activities	Lower-limb′	10	[54, 76]; [24, 58, 84]; [23]; [51, 55, 59, 65]
	Upper-limb (pull-up)	1	[20]
	Whole body″	4	[59]; [15]; [33]; [11]

Notes: the references are organized as follow:
* Straight walking; Walking with change in direction
† Stair descent/ascent; Sit-to-stand
‡ Manual wheelchair transfer; Generic reach; Steering movements
§ Arm elevation and rotation; Elbow flexion and pronation-supination
′ Running; Jumping; Side-cutting maneuvers; Squats
″ Slideboard; Gymnastics; Fencing; Kayak

While the main objective of the MKO has been to obtain accurate joint kinematics by reducing the STA, a unique group of researchers focused on the dissociation of the bone and soft tissue kinematics to estimate the movement of the wobbling mass [24]. These authors state that since the accelerations of the bones and soft tissues are different, it influences the joint dynamics [89, 90]. Moreover, some studies explored other benefits like the ability to use a reduced marker set [15, 64]. Indeed, compared to the methods which model segments independently (*i.e.*, six DoFs each), the joint constraints reduce the number of DoF number in the model. Consequently, fewer markers are required to estimate the joint kinematics. Limited marker sets may be useful when it is anticipated that markers will be occluded by the movement itself (*e.g.*, body in tuck or pike postures).

Only eight studies evaluated the performance of MKO on a pathological population, namely patients with knee osteoarthritis [51, 55], knee ligament deficiency [76, 80], knee prosthesis [49, 66], and cerebral palsy [75, 78]. Pregnant [41, 42], post-menopausal women [67] and elderly [46] were also studied.

4. DISCUSSION

In light of the emerging development and application of MKO algorithms, this article aimed at reviewing the MKO methods and models as well as their validation for estimating upper and lower limb joint kinematics, and their fields of application in terms of activities and outcomes, leading to the following synthesis.

4.1 Methods and models

4.1.1 Implementation

Constrained optimization and Kalman filters can be equivalently implemented as MKO to obtain model-derived joint kinematics. Without joint constraints, MKO is equivalent to SKO and Kalman filters have also already been used in this case (*e.g.*, [91]). However, constrained optimization seems to be more suitable for complex joint models, and closed loops. The choice of the design variables, generalized or natural coordinates, is based on numerical convenience and many have been proposed in the literature. Generalized coordinates (joint angles) are commonly used with hinge or spherical joints and natural coordinates with more advanced joint models such as parallel mechanisms.

Still, velocities and accelerations are rarely included in the state variables [32, 39], although their inclusion ensures that a dynamically consistent solution can be found, which is essential for dynamics.

In addition, with few exceptions [25, 30], constrained optimization is generally performed off-line. Conversely, Kalman filtering is typically a real-time method except in the case of Kalman smoothing [40]. The implementation of constraints in Kalman filters is not trivial unless done through penalty-based methods [11, 37]. Because the state variables include the velocities, accelerations and sometimes the jerks in addition to the generalized coordinates, the Kalman filter provides joint kinematics without discontinuities by integrating the time domain. Nevertheless, many gains (*i.e.*, system and measurement covariance matrices) must be tuned to avoid divergence.

4.1.2 Joint models

One important issue in the MKO is the definition of the joint models. This section summarizes both constraints in the constrained optimization and state variables in the Kalman filters. Other literature reviews, although not systematic nor systematized reviews, have been published on this particular topic where additional upper limb joint models have been listed [2, 92, 93]. In addition, a historical perspective for the introduction of the different lower limb joint models as well as their anatomical significance have been presented [3].

4.1.2.1 Upper limb

The types of joints adopted within upper limb modelling generally include an open-loop kinematic chain including universal sternoclavicular, elbow and wrist joints and a spherical glenohumeral joint [17, 19, 21, 33, 64]. In this case, no acromioclavicular joint was modelled, with only a clavicle segment linking the thorax and humerus. Alternatively, sternoclavicular and acromioclavicular joints were modelled as spherical [13, 18, 27, 43]. Elbow and wrist joints were modelled as hinge and spherical, respectively [14, 35] or both spherical [48, 58, 65]. Additionally, to allow for glenohumeral translations, two studies considered six DoFs [25, 48], while another considered translations as 'soft' constraints [43]. Conversely, closed loops with a scapulothoracic (point(s)-on-ellipsoid) joint [12, 20, 53], and with humeroradial (spherical), humeroulnar (linear annular) and radioulnar (spherical) joints [13] were also proposed. Other joint models relied on the definition of scapular and clavicular rhythms [39, 65].

4.1.2.2 Lower limb

The types of joints selected for lower limb modelling generally include spherical hip, hinge knee and universal ankle joints [11, 22, 25, 32, 42, 60, 62, 66-69]. The universal joint at the ankle was either modelled as concurrent or, more physiologically, non-concurrent axes to account for both talo-crural and subtalar joints [22, 25, 40, 60, 62, 66, 69, 70]. Alternatively, spherical hip, knee and ankle joints have been also widely used in MKO [16, 23, 46, 47, 49, 58, 61, 71], where only the translations were constrained. A unique study modelled the knee joint as universal [26] while another considered six Dofs [31]. Parallel mechanisms or four-bar mechanisms were also proposed as more realistic models for the knee [52, 55, 70, 72] and ankle joints [52, 70, 72], seldom with deformable ligaments [51, 54, 56]. Few studies modelled the knee joint with both tibiofemoral and patelloferomal mechanisms [60, 66, 72]. Other models of knee [40, 65, 74-80] and ankle joints [65, 74, 79] relied on the definition of coupling equations between the flexion-extension and the other DoFs. 'Soft' constraints that defined deformable ligaments with a penalty-based method were also proposed [51, 54, 56]. The minimization of the elastic energy defined by the knee joint stiffness matrix was another penalty implementation [57].

4.3 Validation and performance

The performance of MKO has been assessed using various approaches that can be sorted in six categories of relevance:

i) *Algorithm reliability using simulated data:* The main aim of MKO is to reduce, using *a priori* knowledge of joint mechanisms, the rigid component of the STA (*i.e.*, the rotation and translation of the marker-cluster relative to the bone). This rigid component is the main cause of the joint dislocations obtained in the estimated kinematics [94, 95]. Consequently, we recommend including more realistic STA models (*e.g.*, [96, 97]) when the algorithm reliability is assessed using simulated data, as recently performed by [28]. Also, simulated marker trajectories that derive from models with simplified joint mechanisms, cannot fully illustrate the benefit of MKO over SKO or non-optimized kinematics.

ii) *Residual errors of marker positions:* As discussed by some authors (*e.g.*, [61]), marker residuals may represent the amount of STA but also the adequacy between the kinematic chain (*i.e.*, number of DoFs and geometrical parameters) and the skeleton. Nevertheless, reducing the number of DoFs, *e.g.*, by defining closed-loops [13, 39], without increasing the marker residual may indicate a higher biofidelity of the model. Marker residuals should not be considered as a validation but we recommend providing the range of values with comparison to reported STA range [10].

iii) *Sensitivity analysis:* Sensitivity analyses are essential to evaluate how uncertainties propagate to joint kinematics as well as to determine the geometrical parameters that most affect the model output. These parameters are typically the ones to be personalized. While geometrical parameters may be defined based on medical images [51, 68, 70, 75, 78], this approach is time-consuming and costly for clinical application. Moreover, descriptive anatomy is not always consistent with functional anatomy, especially for complex joints [98]. Development of techniques for non-homogenous scaling [12, 20, 60, 65] and parameters identification before [17, 60] or simultaneously with the motion of interest [14, 16, 22, 62], should be continued. Sensitivity analysis on the numerical parameters of the MKO such as the weights of penalty terms in constrained optimization [56] and covariance of the process noise in Kalman filters should also be generalized.

iv) *Kinematics comparison with various noninvasive methods*: Without joint constraints, MKO is equivalent to SKO. Both differ from non-optimized kinematics (sometimes called direct kinematics [8, 29, 30] although it corresponds to an inverse kinematics approach *stricto sensu*) which is most affected by STA. Most of the differences in the joint kinematics can be attributed to the introduction of the joint constraints but also to the different definition of anatomical frames that can associated to each method [31, 75]. In the comparative studies, differences are usually expressed in terms of root mean square (RMS) differences. Robinson et al. [23] also compared the time histories of the joint angles using statistical parametric mapping [99]. This statistical approach may be more informative about the phases of the movement with large differences between models. The main limitation of comparative studies comes from the lack of a gold standard. Often, the commonly used approach (*e.g.*, non-optimized kinematics) serves as a reference. However, the objective of MKO is to solve limitations coming from commonly used approaches, such as joint dislocation and changes in segment length.

v) As stated by [75], the repeatability of new model needs to be assessed before being introduced clinically. By constraining the joint kinematics to physiological motions, the feasible region is smaller and the solution less sensitive to STA. While Charlton et al. [16] showed that MKO outperforms commonly used models (e.g., Newington–Helen Hayes gait model) in terms of intra-subject and inter-observer repeatability, further studies are required to confirm the clinical relevance of MKO.

vi) *Validation against ground-truth bone kinematics*: While only 12 studies assessed the MKO accuracy against ground-truth bone kinematics, other approaches (*i.e.*, SKO and non-optimized kinematics) also have not extensively been validated using gold standard measurements. The main reason is the scarcity of datasets including several makers (or sensors) and bone kinematics. A recent initiative to provide open source benchmark data [100] should be commended. To evaluate the degree of agreement between model-derived and measured joint kinematics, Richard et al. [57] used a Bland and Altman analysis [101]. Such statistical approaches of agreement may be more informative than root mean squared errors and coefficient of determination. Since only 3 out of the 12 validation studies deal with the upper-limb, such validations should be multiplied in the future.

4.4 Beyond kinematics

In combination with body segment inertial parameters and ground reaction forces, model-derived joint kinematics have been used to calculate joint moments [21, 23, 30, 40, 42, 46, 61, 68, 70, 77, 85] and variables that derive from musculoskeletal models (*e.g.*, musculo-tendon forces or joint contact forces [12, 14, 25, 28, 60, 66, 68, 70, 77, 80, 84, 85]) or in combination with finite-element models (e.g. femoral strain [67]).

Joint constraints reportedly affected less joint kinetics than kinematics [46, 69] in gait, but significant differences were found in side-cutting maneuvers [23] and upper-limb movements [13]. Moreover, STA [28, 77] and joint constraints [70, 84] had an effect on musculo-tendon and joint contact forces. Kalman filters compared to constrained optimization can lead to more physiological joint moments [40]. While about 17% of the studies reported musculoskeletal variables, additional 30% introduced or discussed the need of MKO for musculoskeletal applications. Unless when Kalman filters are used [40] or when wobbling masses are specifically included in the modelling [89], MKO generally has a limited effect on joint moments. The main effect on musculo-tendon and joint contact forces seems to come directly from the number of DoFs of the musculoskeletal model [70, 84, 102-104] and this has to be taken into account when defining the joint models.

5. CONCLUSION

This systematized review has highlighted a variety of MKO algorithms and of joint models, including advanced mechanisms, especially for the knee and shoulder joints. However, the ability of MKO to accurately estimate joint kinematics depends on both models (*e.g.*, joint constraints, geometrical parameters, *etc.*) and methods (*e.g.*, weighting, initial condition, *etc.*) to prevent deleterious effects of STA on the secondary degrees-of-freedom, often associated to pathologies. Model personalization requires further developments to better estimate these secondary DoFs. MKO has been assessed in several ways but only 12 out of 74 studies included validation against ground-truth bone kinematics. Additional validations, especially for the upper-limb, should be undertaken.

We recommend a more systematic approach for the evaluation of the MKO algorithms, in agreement with the best practices proposed for musculoskeletal models [105, 106]: (i) Assess the biofidelity of the joint model using gold standard data of the movement of interest when possible as in Seth et al. [39]; (ii) Test the robustness of the model and of the method by evaluating the sensitivity of the joint kinematics to both geometrical and numerical parameters and to STA; (iii) Ensure that the marker residuals remain within the STA range reported in the literature [10]; (iv) Compare resulting joint kinematics to those already available in the literature; (v) Blindly validate MKO using datasets with both ground-truth bone and skin marker kinematics as provided in Cereatti et al. [100] when possible; and (vi) Assess the repeatability and reliability of the method for clinical applications.

Finally, we encourage authors to use the expression ‘multibody kinematics optimization’ to better track its evolution and benefit in future reviews and to avoid confusion with other well-established names in various fields such as ‘global optimization’ and ‘inverse kinematics’.

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6. Acknowledgement

The authors acknowledge Denis Arvisais for his help in the database search.

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Table Caption List

Appendix 1

Table S1

Article	Questions														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Aguiar et al. (2014) [42]	1	2	2	2	2	2	2	0	2	/	1	1	0	1	1
Aguiar et al. (2016) [41]	2	2	2	1	2	2	1	1	2	2	2	1	0	1	1
Andersen et al. (2009) [32]	1	1	2	2	/	2	/	2	2	/	1	1	2	1	1
Andersen et al. (2010) [81]	2	2	2	1	2	2	2	2	2	1	2	2	1	2	2
Andersen et al. (2010) [62]	1	1	2	2	0	2	2	2	2	1	1	1	1	1	1
Ausejo et al. (2011) [50]	2	2	2	2	2	2	2	1	1	/	2	1	0	0	1
Ayusawa et al. (2014) [14]	2	2	2	2	0	1	2	1	1	/	1	1	0	0	1
Begon et al. (2008) [15]	2	2	2	2	1	2	2	2	2	2	2	2	0	2	2
Begon et al. (2016) [27]	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2
Bolsterlee et al. (2014) [12]	2	2	2	2	2	1	1	2	2	1	2	2	2	1	2
Bonnechère et al. (2015) [74]	2	2	0	1	2	2	2	0	2	2	2	2	1	1	2
Cerveri et al. (2003) [35]	2	2	2	2	1	1	2	2	2	/	1	2	0	0	2
Cerveri et al. (2003) [33]	2	1	2	2	1	1	2	0	2	/	1	2	1	2	2
Cerveri et al. (2005) [34]	2	2	2	2	/	0	/	2	2	2	2	2	0	1	1
Charbonnier et al. (2014) [43]	2	2	2	1	2	2	2	2	2	/	2	2	1	2	2
Charlton et al. (2004) [16]	1	2	2	2	0	1	2	2	2	1	2	2	1	2	2
Clément et al. (2015) [51]	2	2	2	2	2	2	2	2	2	1	2	2	2	2	2
Clément et al. (2017) [55]	2	2	0	1	2	2	2	2	1	2	2	2	2	2	2
Debril et al. (2011) [64]	2	2	2	1	2	2	2	2	2	1	2	2	1	1	2
De Groote et al. (2008) [40]	2	2	2	1	1	2	1	1	1	/	2	2	2	2	2
Duprey et al. (2010) [52]	2	2	2	2	2	0	1	2	1	/	2	2	2	1	2
El Habachi et al. (2015) [53]	2	2	2	2	2	2	2	2	2	1	2	2	2	2	2
El Habachi et al. (2015) [72]	2	2	2	1	2	2	1	2	2	1	2	2	2	1	1
El-Gohary & McNames (2012) [36]	1	2	2	2	1	2	2	2	1	2	2	2	0	1	2
Fohanno et al. (2013) [17]	2	2	1	1	2	2	2	1	2	2	2	2	0	2	2
Fohanno et al. (2014) [11]	2	2	2	1	2	2	2	2	2	2	1	2	1	2	2
Gasparutto et al. (2015) [54]	2	2	1	0	2	2	2	2	1	/	2	2	2	2	2
Groen et al. (2012) [71]	2	2	2	1	2	1	2	1	0	2	2	2	2	2	2
Jackson et al. (2012) [18]	2	2	1	1	2	2	2	1	1	2	2	2	1	2	1
Kaintz et al. (2016) [75]	2	2	1	0	2	2	2	2	1	2	2	2	1	2	2
Klous & Klous (2010) [44]	2	2	2	1	/	1	/	/	2	2	2	2	1	2	2
Koning et al. (2015) [59]	2	2	2	1	2	2	2	2	2	/	2	2	2	2	2
Kun et al. (2011) [88]	2	2	1	2	2	2	2	2	2	/	2	2	0	0	1
Laitenberger et al. (2015) [13]	2	2	2	2	2	2	2	2	2	/	2	2	2	2	2
Lamberto et al. (2016) [28]	2	2	1	1	2	2	2	2	2	2	2	2	2	2	1
Lathrop et al. (2011) [31]	2	2	2	2	1	1	2	2	1	/	2	2	2	2	2
Lee et al. (2010) [58]	2	2	2	2	0	1	0	0	2	/	1	1	0	0	1
Li et al. (2012) [76]	2	2	2	1	2	2	2	2	2	2	2	2	2	2	1

Article (continued)	Questions														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Lisco et al. (2016) [63]	1	2	2	1	1	2	2	1	0	2	2	1	0	0	1
Lu & O'Connor (1999) [45]	2	2	2	2	0	0	1	1	1	/	2	2	0	0	1
Lund et al. (2015) [60]	2	2	2	1	2	1	1	2	2	/	2	2	1	2	2
Mantovani & Lamontagne (2017) [29]	2	2	2	1	2	2	2	2	0	2	2	2	2	2	2
Marra et al. (2015) [66]	2	2	1	1	2	2	/	2	2	/	2	2	2	2	2
Martelli et al. (2015) [68]	2	2	1	1	2	1	1	1	1	/	2	2	2	2	2
Martelli et al. (2015) [67]	2	2	1	1	2	2	2	2	1	2	2	2	2	2	2
Miezal et al. (2016) [37]	1	1	2	1	2	1	2	1	1	/	1	2	0	1	1
Mokhtarzadeh et al. (2014) [84]	2	2	1	2	2	2	2	1	2	2	2	2	2	2	2
Moniz-Pereira et al. (2014) [46]	2	2	0	1	1	2	2	1	1	/	2	2	2	2	2
Myers et al. (2015) [77]	2	2	2	0	2	2	1	1	2	1	2	2	2	2	2
Ojeda et al. (2014) [47]	2	2	2	2	1	1	1	2	2	/	2	1	2	1	2
Ojeda et al. (2016) [61]	2	2	2	2	1	1	2	2	1	/	2	2	0	2	2
Pizzolato et al. (2017) [30]	2	2	1	2	2	2	1	1	1	/	2	2	1	2	2
Pontonnier & Dumont (2009) [19]	2	2	2	2	0	1	0	/	1	/	2	1	0	1	1
Pontonnier & Dumont (2010) [73]	1	2	2	2	0	1	2	/	2	/	2	1	1	1	1
Prinold & Bull (2014) [20]	1	2	2	2	1	1	1	1	2	2	2	2	0	2	2
Prokopenko et al. (2001) [21]	2	2	2	2	2	2	2	2	2	2	1	2	0	2	2
Reinbolt et al. (2005) [22]	0	2	2	2	0	1	1	2	2	/	2	2	2	2	2
Reinbolt et al. (2007) [69]	0	2	2	2	2	2	1	2	2	2	2	2	1	1	2
Richard et al. (2016) [57]	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Robinson et al. (2014) [23]	2	2	2	2	2	2	2	2	1	2	2	2	2	2	2
Roux et al. (2002) [48]	2	2	1	2	/	2	/	2	2	/	2	2	0	1	2
Sancisi et al. (2017) [56]	2	1	2	2	1	2	1	1	2	/	1	1	1	2	2
Scheys et al. (2011) [78]	2	2	2	1	2	2	2	1	2	2	2	2	1	1	2
Seth et al. (2016) [39]	2	2	2	2	1	2	1	2	2	/	2	2	2	1	2
Sholukha et a. (2006) [79]	0	2	2	2	2	2	2	2	2	1	1	2	1	2	1
Sholukha et al. (2013) [65]	1	1	1	0	1	1	1	0	1	/	1	1	1	2	1
Stagni et al. (2009) [49]	2	2	1	1	2	2	1	2	1	2	2	2	0	2	2
Thouzé et al. (2016) [24]	2	2	2	1	2	2	2	1	2	2	2	2	2	2	2
Tsai & Lung (2014) [26]	2	2	2	2	0	0	1	0	2	/	1	2	0	0	2
Valente et al. (2014) [85]	2	2	1	1	2	2	2	2	1	2	2	2	2	1	2
Valente et al. (2015) [70]	2	2	1	1	2	2	2	2	1	2	2	2	2	2	2
van den Bogert et al. (2013) [25]	2	2	2	2	2	2	2	0	2	/	2	2	1	2	2
Zhang et al. (2011) [38]	0	2	2	2	0	2	2	2	1	/	2	2	0	1	2
Zheng et al. (2014) [80]	2	2	1	1	1	2	2	2	1	/	2	2	2	1	1