Annexe A

Glossaire

La plupart des termes du glossaire sont définis à partir du Grand Dictionnaire Terminologique (http://www.granddictionnaire.com)

Glossaire relatif à la partie médicale

Agénésie : Non développement d'un tissu, d'un organe ou d'une partie du corps.

Amyotrophie : Diminution de volume d'un muscle, pouvant être d'origine nerveuse ou musculaire, ou due à une immobilisation prolongée ou à un traitement médicamenteux.

Amyotrophie spinale : Terme générique sous lequel on regroupe actuellement les affections dégénératives lentes des motoneurones de la corne antérieure. Cette pathologie se traduit généralement par des faiblesses musculaires.

Analyse Quantifiée de la Marche : Examen médical permettant de quantifier la marche d'un patient par des variables biomécaniques (cinématique, cinétique, électromyographie). Le but de cet examen est d'identifier et de comprendre les défauts de marche du patient le réalisant dans un objectif thérapeutique.

Arthrogrypose : Affection congénitale rare, parfois héréditaire, caractérisée par des raideurs articulaires et des déformations des membres, une amyotrophie, et des fossettes cutanées en regard des articulations atteintes.

Contracture : Raccourcissement d'un ou de plusieurs muscles qui occasionne une résistance élevée aux mouvements passifs et une limitation de l'amplitude articulaire.

Digitigrade : Sur la pointe des pieds (utilisé en zoologie pour qualifier un animal marchant en s'appuyant sur les doigts de pied et non sur le pied lui-même).

Dysplasie : Malformation ou déformation résultant d'une anomalie du développement d'un tissu ou d'un organe.

Dystrophie Musculaire : Terme générique sous lequel on regroupe un certain nombre d'affections héréditaires dégénératives progressives des muscles striés.

Equin : Hyperextension du pied sur la jambe.

Hémiplégie : Paralysie totale ou partielle d'un hémicorps par atteinte centrale du faisceau pyramidal, dont les signes sont variables en fonction du niveau de la lésion.

Infirmité Motrice Cérébrale (IMC): Anomalie non évolutive et non curable des tissus cérébraux, survenant avant, pendant ou peu de temps après la naissance et se manifestant entre autres par des troubles moteurs.

Myopathie : Terme général, qui désigne toute atteinte musculaire, qu'elle soit localisée ou généralisée, sans égard à son origine.

Neuropathie : Terme générique donné à toutes les affections du système nerveux.

Neuropathie périphérique : Affection du système nerveux périphérique caractérisée par un déficit sensitif, une faiblesse et une atrophie musculaire, une diminution des réflexes ostéotendineux et des symptômes vasomoteurs.

Ostéochondrite : Affection non inflammatoire des épiphyses, ostéonécrose qui cause des douleurs et des déformations au niveau des os.

Pied bot : Déformation permanente du pied, congénitale ou acquise, qui l'empêche de prendre contact avec le sol sur ses points d'appui normaux de la région plantaire.

Pied bot varus équin (PBVE) : Pied bot caractérisé par une extension et une rotation interne du pied qui repose au sol sur le bord extérieur de sa pointe.

Pied creux : Déformation du pied, généralement acquise, qui est caractérisée par une cambrure plantaire exagérée.

Scoliose : Déviation latérale de la colonne vertébrale.

Spasticité : Accroissement anormal du tonus musculaire dû à une lésion de la voie pyramidale, qui se traduit par une rigidité musculaire et une exagération des réflexes ostéotendineux.

Spina bifida : Malformation du système nerveux central caractérisée par une absence de fermeture de l'arc vertébral postérieur, du tube neural et de la peau, siégeant habituellement au niveau de la région lombo-sacrée.

Synostose : Union, congénitale ou acquise, de deux pièces osseuses, primitivement ou normalement séparées.

Glossaire relatif à la partie extraction de connaissances

Apprentissage automatique : Processus par lequel un ordinateur accroît ses connaissances et modifie son comportement à la suite de ses expériences et de ses actes passés.

Apprentissage non-supervisé : Apprentissage par lequel un programme peut, par inférence, découvrir seul de nouveaux concepts, trouver de nouvelles lois, de nouveaux faits.

Apprentissage supervisé : Apprentissage par lequel un programme découvre de nouvelles lois capables de classer correctement les exemples de l'ensemble d'apprentissage mais aussi des exemples nouveaux ne faisant pas partie de cet ensemble.

Arbre de décision : Outil d'aide à la décision qui se présente sous la forme de représentation graphique d'un processus décisionnel, incluant les résultats possibles d'une décision.

> *Anatomie de l'arbre de décision :* Chaque arbre est constitué de **branches**, de **nœuds** et de **feuilles**. Un nœud représente une séparation en deux ou plusieurs branches. Une feuille représente la fin d'une branche. Le parcours d'une branche peut être représenté sous la forme d'une règle où chaque nœud correspond à une condition de la règle. La feuille correspond à la conclusion de la règle.

Attribut : Variable qualitative décrivant un objet ou un individu.

Base de connaissances : Dans notre travail, correspond à l'édition de règles interprétables et significatives d'une base de règles afin d'apporter du savoir à un domaine.

Base de règles : Elément d'un système d'aide à la décision qui contient l'ensemble des règles générées par un expert ou un apprentissage automatique.

Classe : Sous-ensemble résultant de la division d'un ensemble donné en parties disjointes, qui peut également être appelé groupe.

Connaissance : Elément du savoir d'un domaine.

Ensemble d'apprentissage : Ensemble des exemples servant à l'apprentissage supervisé.

Entropie : En théorie de l'information, mesure de la perte d'information causée par les erreurs dues au hasard.

Exemple : Individu de l'ensemble d'apprentissage dont l'appartenance à un groupe ou à une classe est connu.

Extraction de Connaissances à partir de Données (ECD) : Processus qui consiste à induire automatiquement des connaissances à partir d'une base de données englobant différentes étapes qui vont de la sélection des données à l'interprétation des connaissances. Plus largement appelé "*Knowledge Discovery in Database*" (KDD) en anglais ou "*datamining*" dans certains cas.

Flou : Imprécis, dont la frontière n'est pas nette et dont l'appartenance à un ensemble est une question de degré.

> *Logique floue :* Logique non classique pour laquelle il existe un continuum de possibilités allant du vrai au faux, tant pour des faits que pour des relations.
>
> *Ensemble flou :* Ensemble dont l'appartenance des membres est déterminée au moyen de degrés d'appartenance.

Fouille de données : Etape spécifique de l'ECD qui fait référence à l'algorithme utilisé pour induire des connaissances, appelée "*dataming*" en anglais.

Heurisitique : Technique consistant à apprendre petit à petit, en tenant **compte** de ce qui a été fait précédemment pour tendre **vers** la solution d'un problème.

Individu : Élément représentant un phénomène (personne, objet, concept, évènement) et qui peut être traité comme une unité indépendante et à propos duquel des données peuvent être stockées.

Interprétabilité (d'une règle) : Fait référence à l'aptitude d'une personne experte ou non-experte à pourvoir lire, comprendre et utiliser aisément une règle dans son domaine.

Raisonnement : Forme d'activité mentale consistant à effectuer un enchaînement logique, à partir de propositions de départ, afin d'en arriver à une conclusion.

Raisonnement par abduction : Consiste à déterminer les causes susceptibles d'expliquer un fait en remontant des conclusions aux hypothèses.

Raisonnement par analogie : Consiste à affecter une ou plusieurs propriétés à un objet sachant qu'un objet de référence la (les) possède déjà.

Raisonnement inductif : Consiste à aller du singulier au général et des effets à la cause.

Raisonnement déductif : Consiste à conclure à partir d'hypothèses, de prémisses.

Règle "Si-Alors" : Spécifie une relation logique parmi un ensemble de faits, et qui comprend une partie « si », représentant la prémisse ou la condition, et une partie « alors », représentant l'action à prendre si la prémisse est vraie.

Patron (de mouvement) : Organisation dynamique caractéristique du corps ou d'un de ses segments (en anglais : *pattern*).

Précision : Capacité d'un test, d'un examen ou d'une méthode à classer correctement des individus.

Sensibilité : Capacité d'un test ou d'un examen à d'identifier les sujets qui sont atteints d'une maladie ou d'une anomalie donnée.

Spécificité : Capacité d'un test ou d'un examen à d'identifier les sujets qui ne sont pas atteints d'une maladie ou d'une anomalie donnée.

Système expert : Application capable d'effectuer dans un domaine des raisonnements logiques comparables à ceux que feraient des experts humains.

Taux d'explication : Mesure la capacité d'explication d'un phénomène par au moins une règle.

Valeur de vérité (d'une règle) : Niveau de confiance accordée à une règle.

Variable linguistique : Communément définie par un triplet constitué de la variable, de l'ensemble des valeurs prises par cette variable et de l'ensemble des sous-ensembles flous associés aux dénominations linguistiques.

Annexe B

Rapport type d'une Analyse Quantifiée de la Marche (AQM)

Les pages suivantes présentent le rapport type d'une Analyse Quantifiée de la Marche.

Dans l'ordre des pages :

- Compte rendu de l'AQM,
- Reproductibilité des passages,
- Moyenne des paramètres cinématiques (Angles articulaires normalisés par rapport au cycle de marche),
- Moyenne des paramètres cinétiques (Moments internes normalisés par rapport au cycle de marche),
- Moyenne des paramètres spatio-temporaux, forces de réaction au sol et des puissances internes (normalisés par rapport au cycle de marche),
- Cinématique du passage retenu (dans un rapport standard, la cinétique d'un passage type est également retenu),
- Paramètres électromyographiques présentés sur plusieurs cycles de marche,
- Bilan clinique.

Patient X
Adresse

Tél :

Taille : 137 cm **Poids : 24,5 kg**

Diagnostic : Hémiplégie gauche

Enfant adressé par le Docteur Dr X

ANALYSE QUANTIFIEE DE LA MARCHE DU 03/02/2004 (1er examen)

- Enregistrement vidéo
- Analyse cinématique et cinétique
- EMG : grands fessiers, moyens fessiers, droits antérieurs, vastes internes, ischio-jambiers, triceps, péroniers et jambiers antérieurs.
- Analyse de la reproductibilité
- Analyse de la moyenne

RESULTATS DE L'EXAMEN

Marche reproductible.

I – PARAMETRES SPATIO-TEMPORAUX

Marche asymétrique avec une phase d'appui plus importante à droite qu'à gauche.
La phase d'appui à gauche représente 57 % du cycle de marche 62 % du cycle de marche à droite.
La vitesse de marche est de 1,1 m/s.
La cadence est de 119 pas/mn.
La longueur du pas est de 58 cm à droite et de 54 cm à gauche.

II – ANALYSE DES FORCES D'APPUI DU PIED SUR LE SOL

La **composante antéro-postérieure** est correcte.
La **composante médio-latérale** est correcte
La **composante verticale** est correcte
Les **courbes de déroulement du pas** indiquent une attaque juste en arrière des métatarses et un décollement par les orteils à gauche. A droite, l'attaque du pas se fait juste en avant de la malléole et le décollement par les orteils.

III – ANALYSE CINEMATIQUE ET CINETIQUE

- Pieds :
Attaque du pas avec une flexion plantaire de 10° supérieure à la norme à gauche.
Tendance anormale vers la flexion dorsale à l'attaque du pas à gauche.
Flexion dorsale inférieure à la norme en fin d'appui à gauche.
Rotation du pied par rapport au tibia de 20° vers l'extérieur à droite.
Moment d'extension permanent et biphasique à gauche.
Valeur du moment d'extension légèrement supérieure à la norme à droite en fin d'appui.
Absorption d'énergie légèrement supérieure à la norme en début d'appui à gauche.
Energie propulsive inférieure à la norme à gauche et supérieure à la norme à droite.

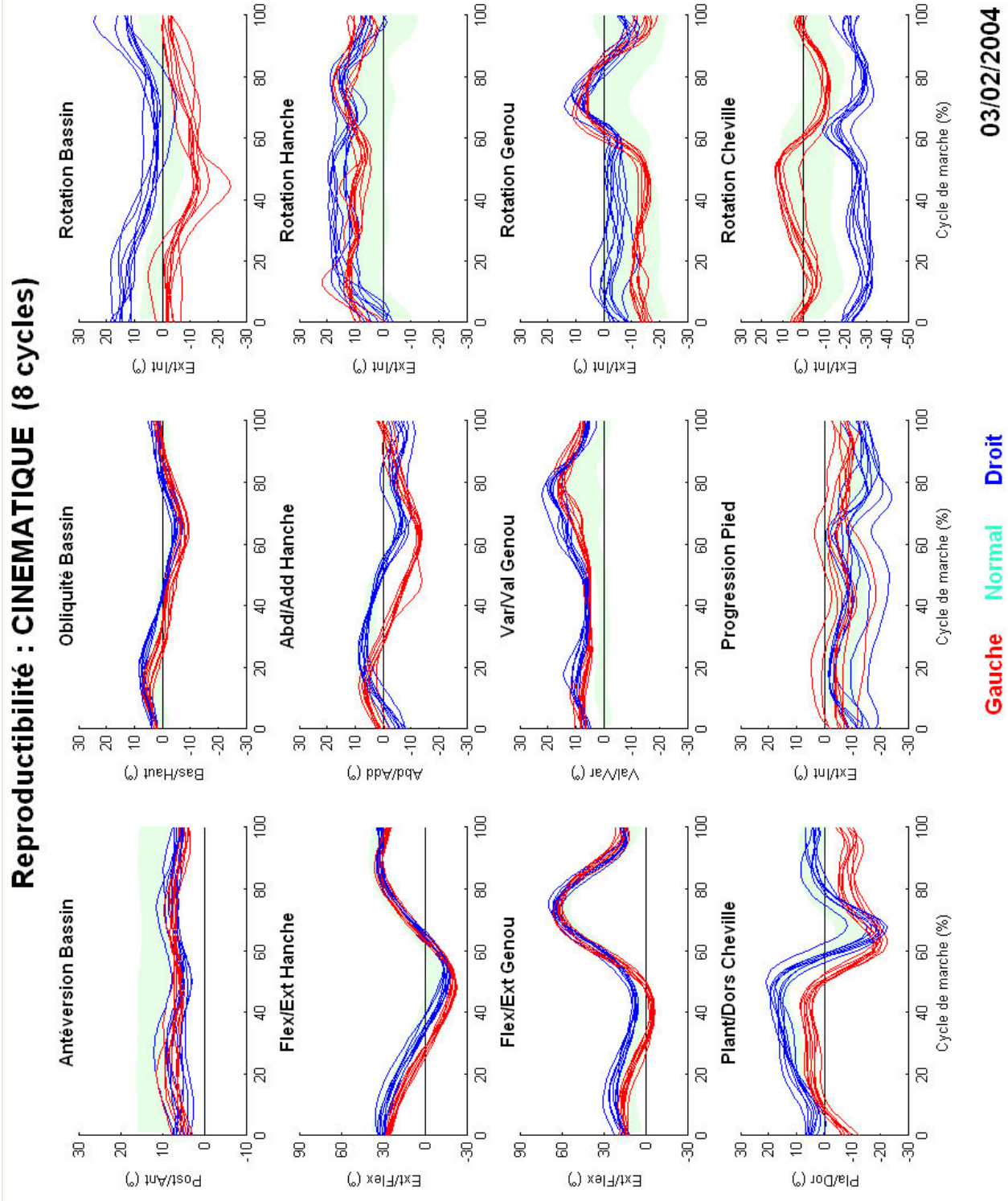
- Genoux :
Attaque du pas avec une flexion légèrement supérieure à la norme aussi bien à gauche qu'à droite.
Extension supérieure à la norme en milieu d'appui à gauche.
Moment extenseur inférieur à la norme en début d'appui à gauche.
Moment fléchisseur supérieur à la norme en milieu d'appui à gauche.
Génération d'énergie supérieure à la norme en fin d'appui à gauche.

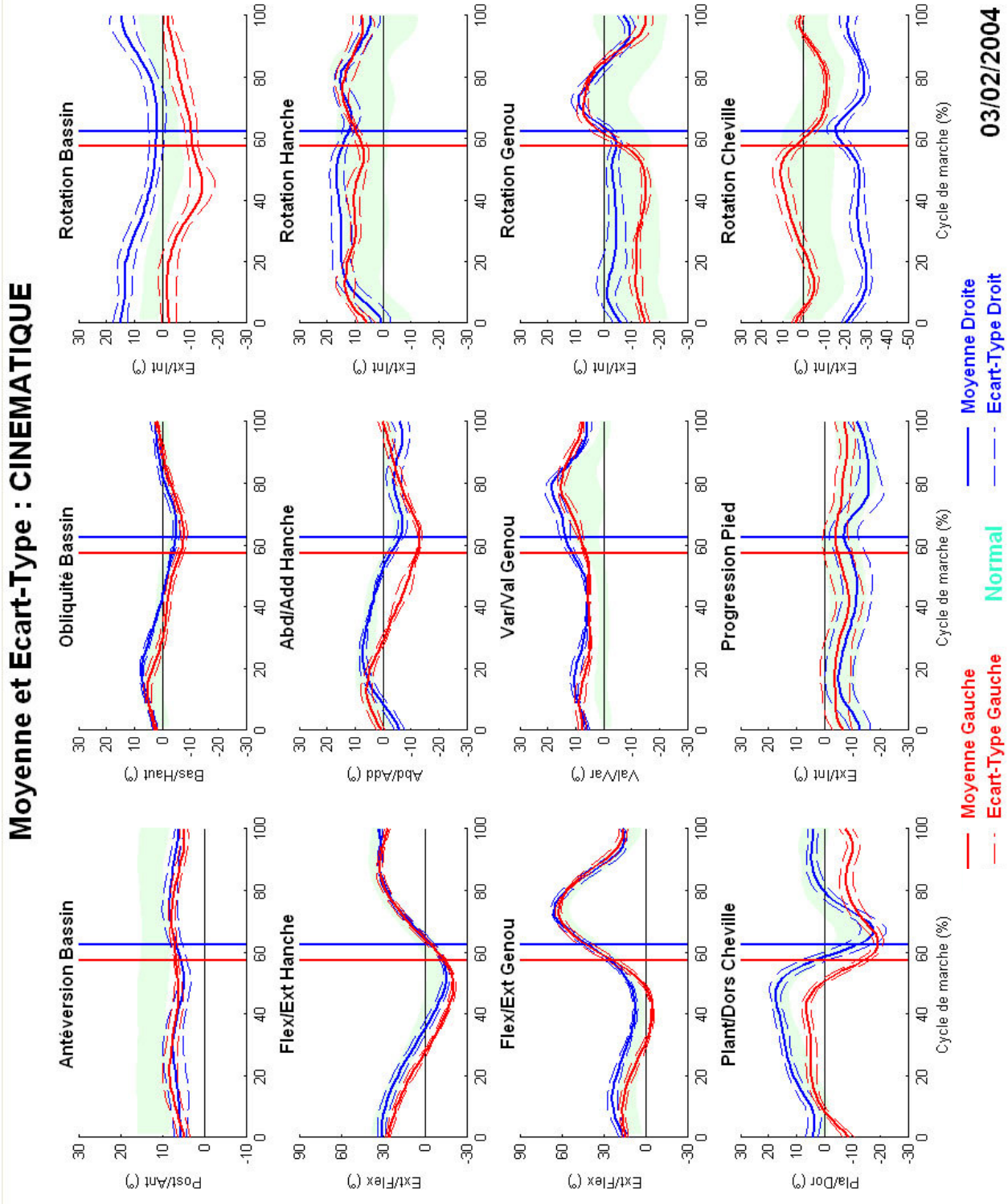
- Hanche :
Extension légèrement supérieure à la norme en fin d'appui notamment à gauche.
Abduction supérieure à la norme en fin d'appui à gauche.
Moment de flexion/extension correct.
Moment d'abduction avec des valeurs inférieures à la norme à gauche et supérieures à la norme à droite en fin d'appui.
Echange énergétique correct.

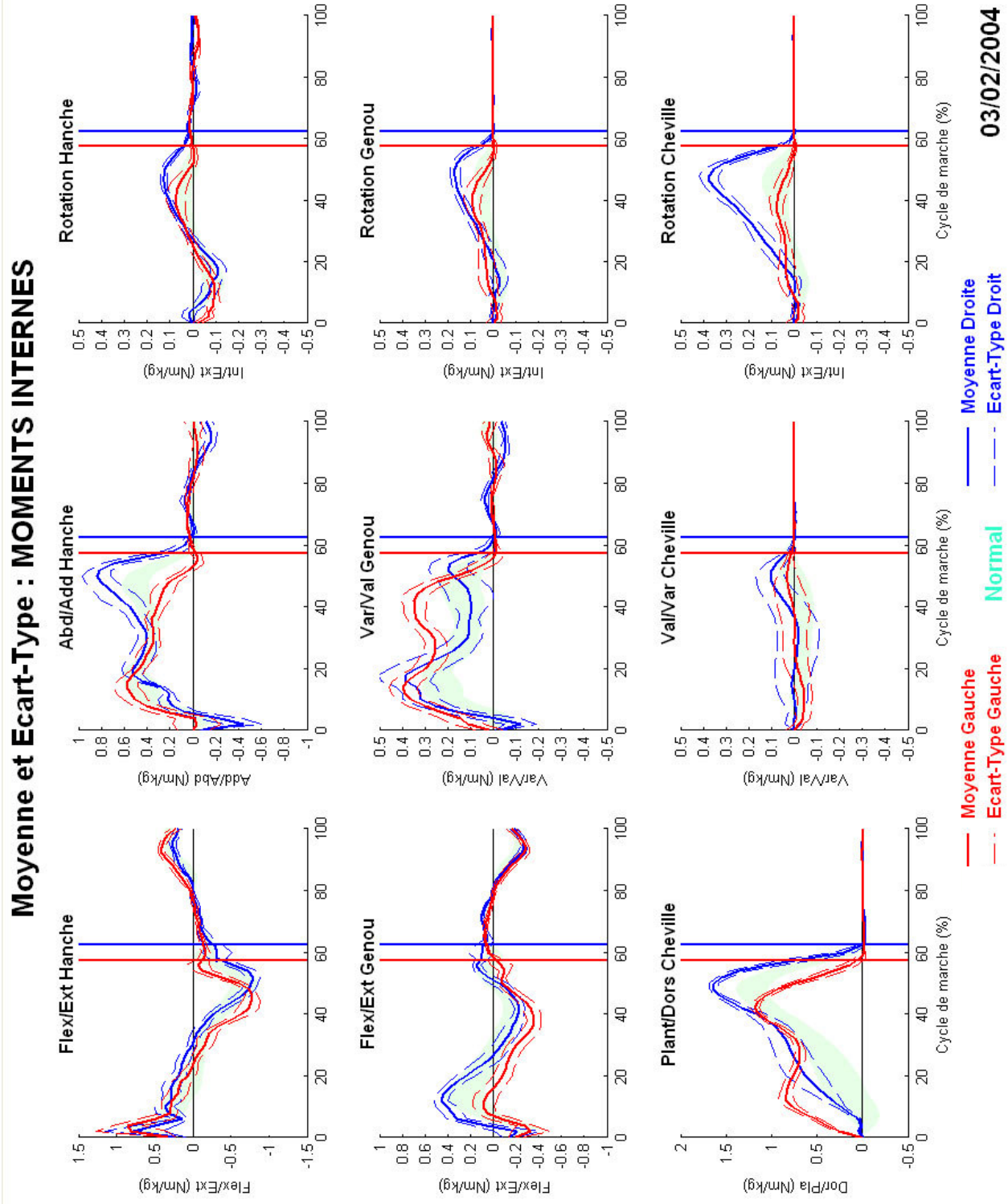
- Bassin
Antéversion de 5° inférieure à la norme.
Rotation de l'hémi-bassin droit vers l'intérieur et de l'hémi-bassin gauche vers l'extérieur.

IV – ANALYSE DE L'ACTIVITE ELECTROMYOGRAPHIQUE

MUSCLES	**MEMBRE INFERIEUR GAUCHE**	**MEMBRE INFERIEUR DROIT**
Grands fessiers	Activité légèrement prolongée	Activité anormale fin d'appui/début de phase oscillante
Moyens fessiers	Activité correcte	Activité correcte
Droits antérieurs	Léger manque de relâchement en phase d'appui et activité prolongée en milieu de phase oscillante	Activité correcte
Vastes internes	Activité correcte	Activité correcte
Ischio-jambiers internes	Activité permanente	Activité légèrement prolongée
Triceps	Activité prématurée	Activité correcte
Courts péroniers	Activité prématurée	Léger manque de relâchement en phase oscillante
Jambiers antérieurs	Activité permanente	Léger manque de relâchement en phase d'appui


Reproductibilité : CINEMATIQUE (8 cycles)
03/02/2004
Gauche
Normal
Droit
Antéversion Bassin
Oblicuité Bassin
Rotation Bassin
Flex/Ext Hanche
Abd/Add Hanche
Rotation Hanche
Flex/Ext Genou
Var/Val Genou
Rotation Genou
Plant/Dors Cheville
Progression Pied
Rotation Cheville
Post/Ant (°)
Bas/Haut (°)
Ext/Int (°)
Ext/Flex (°)
Abd/Add (°)
Val/Var (°)
Pla/Dor (°)
Cycle de marche (%)


Moyenne et Ecart-Type : CINEMATIQUE
03/02/2004
Antéversion Bassin
Oblicuité Bassin
Rotation Bassin
Flex/Ext Hanche
Abd/Add Hanche
Rotation Hanche
Flex/Ext Genou
Var/Val Genou
Rotation Genou
Plant/Dors Cheville
Progression Pied
Rotation Cheville
Post/Ant (°)
Bas/Haut (°)
Ext/Int (°)
Ext/Flex (°)
Abd/Add (°)
Ext/Int (°)
Ext/Flex (°)
Val/Var (°)
Ext/Int (°)
Pla/Dor (°)
Ext/Int (°)
Ext/Int (°)
Cycle de marche (%)
Cycle de marche (%)
Cycle de marche (%)
Moyenne Gauche
Ecart-Type Gauche
Normal
Moyenne Droite
Ecart-Type Droit

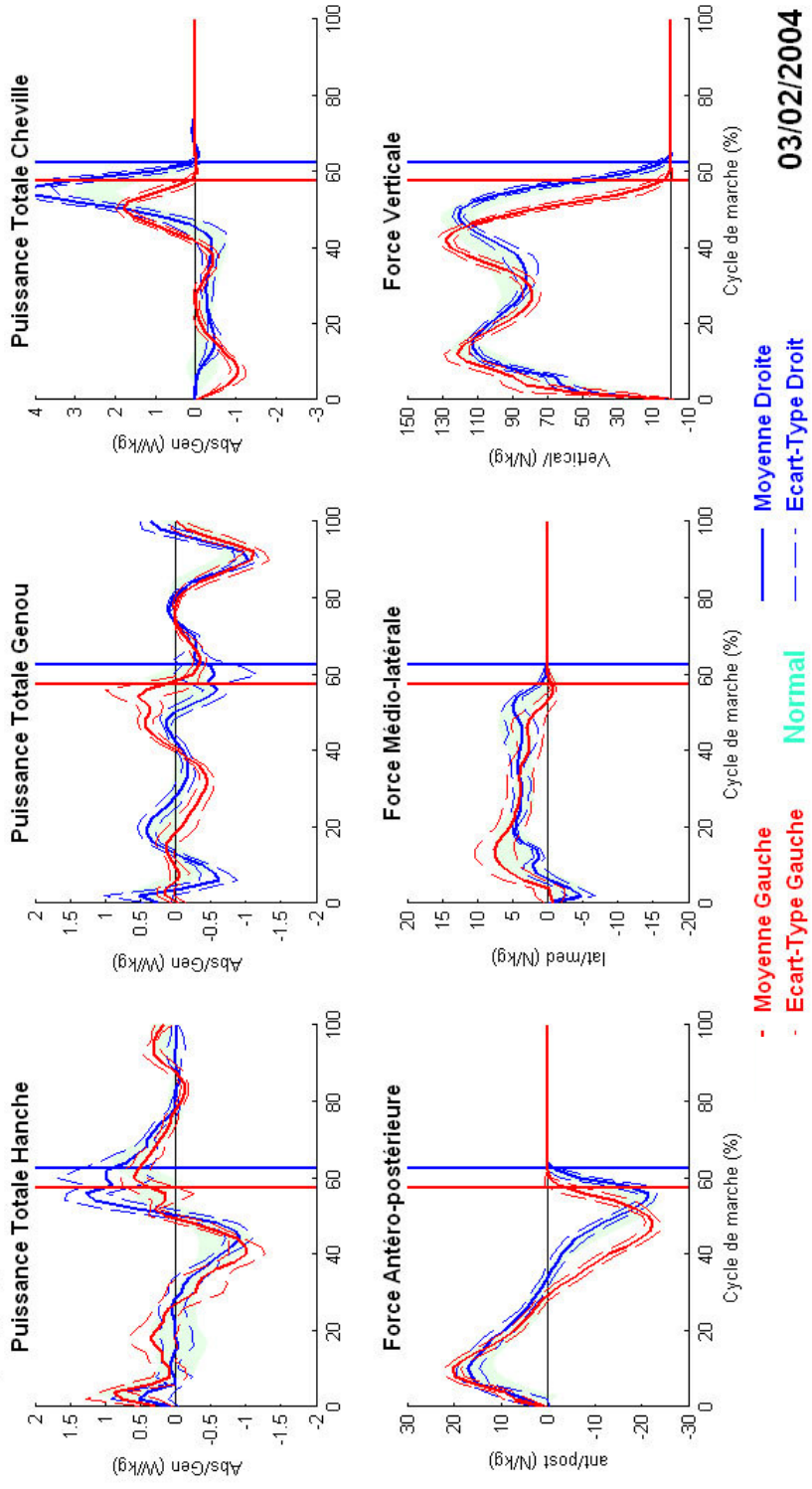

Moyenne et Ecart-Type : MOMENTS INTERNES
03/02/2004
Flex/Ext Hanche
Abd/Add Hanche
Rotation Hanche
Flex/Ext Genou
Var/Val Genou
Rotation Genou
Plant/Dors Cheville
Val/Var Cheville
Rotation Cheville
Flex/Ext (Nm/kg)
Add/Abd (Nm/kg)
Int/Ext (Nm/kg)
Dor/Pla (Nm/kg)
Var/Val (Nm/kg)
Cycle de marche (%)
Moyenne Gauche
Ecart-Type Gauche
Normal
Moyenne Droite
Ecart-Type Droit

Moyenne et Ecart-Type : SPATIO-TEMPORAUX, PUISSANCES, FORCES

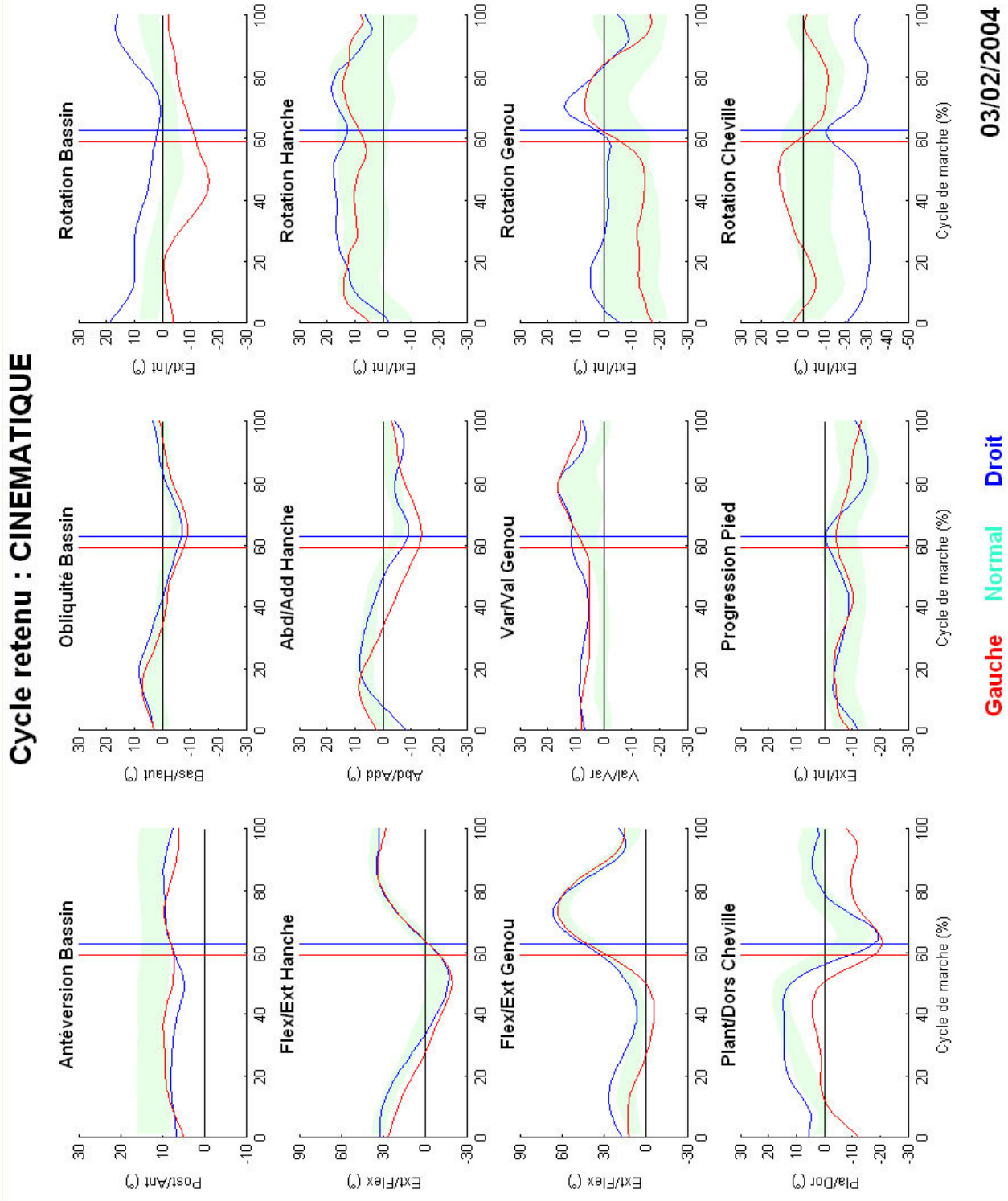
Paramètres Spatio-temporaux

Moyenne ± Ecart-Type

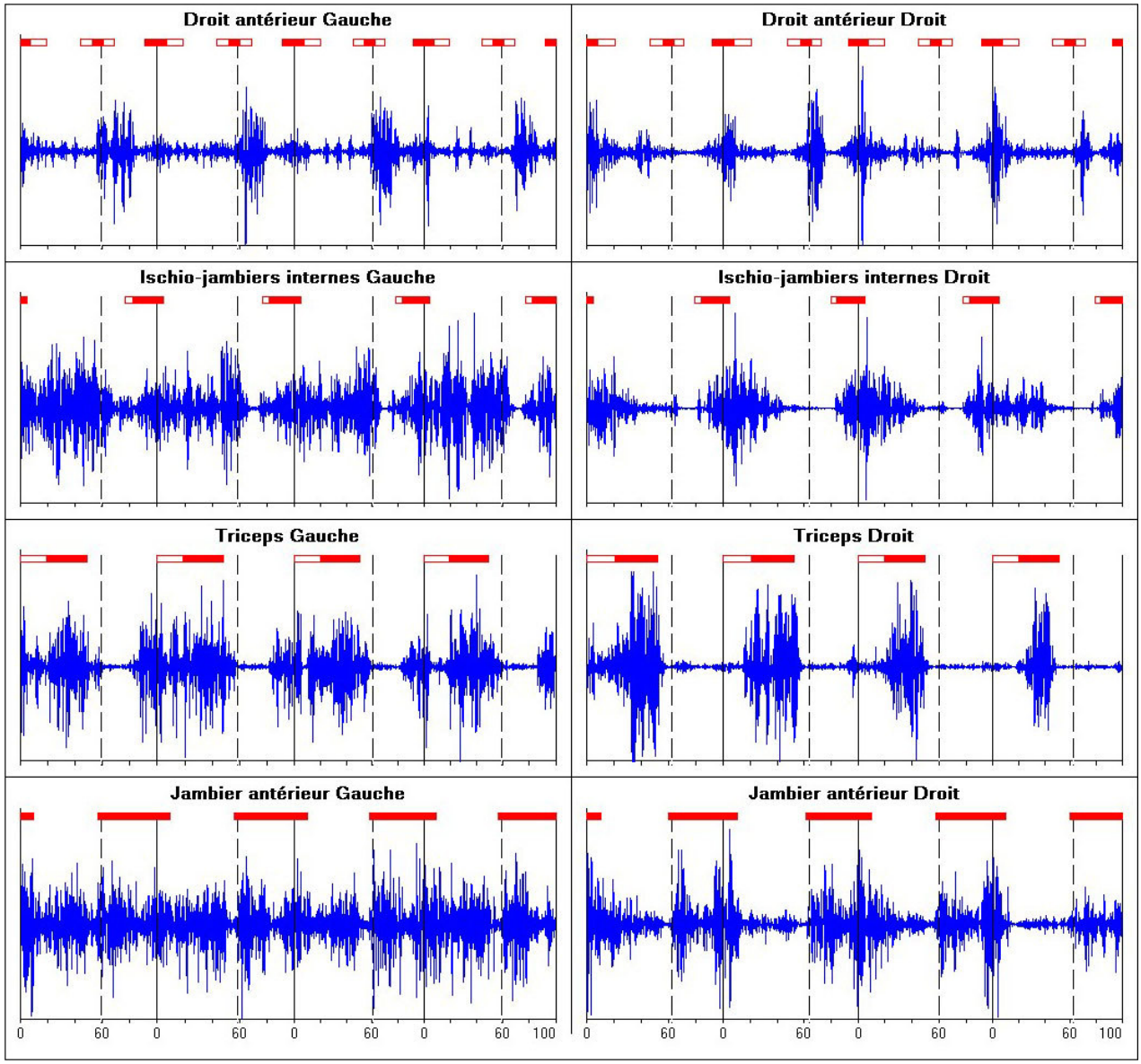
	Droit	Gauche	Normal
Vitesse (m/s)	1.1 ±0.07	1.1 ±0.05	1 ±0.1
Cadence (pas/min)	119 ±5.1	119 ±5	124 ±14.7
Longueur pas (m)	0.58 ±0.01	0.54 ±0.03	0.51 ±0.05
Longueur cycle (m)	1.12 ±0.04	1.12 ±0.03	0.99 ±0.09
Temps pas (s)	0.46 ±0.01	0.53 ±0.01	0.49 ±0.02
Temps cycle (s)	1 ±0.04	1 ±0.04	0.97 ±0.11
Lever pied (%)	62 ±1.8	57 ±1.3	60 ±2.4
Lever pied opposé (%)	10 ±1.4	9 ±1.2	9 ±2
Contact pied opposé (%)	53 ±1.3	46 ±1.9	50 ±2
Double appui (%)	20 ±2.2	20 ±1.7	20 ±3.1
Simple appui (%)	42 ±1.9	37 ±2	40 ±1.9

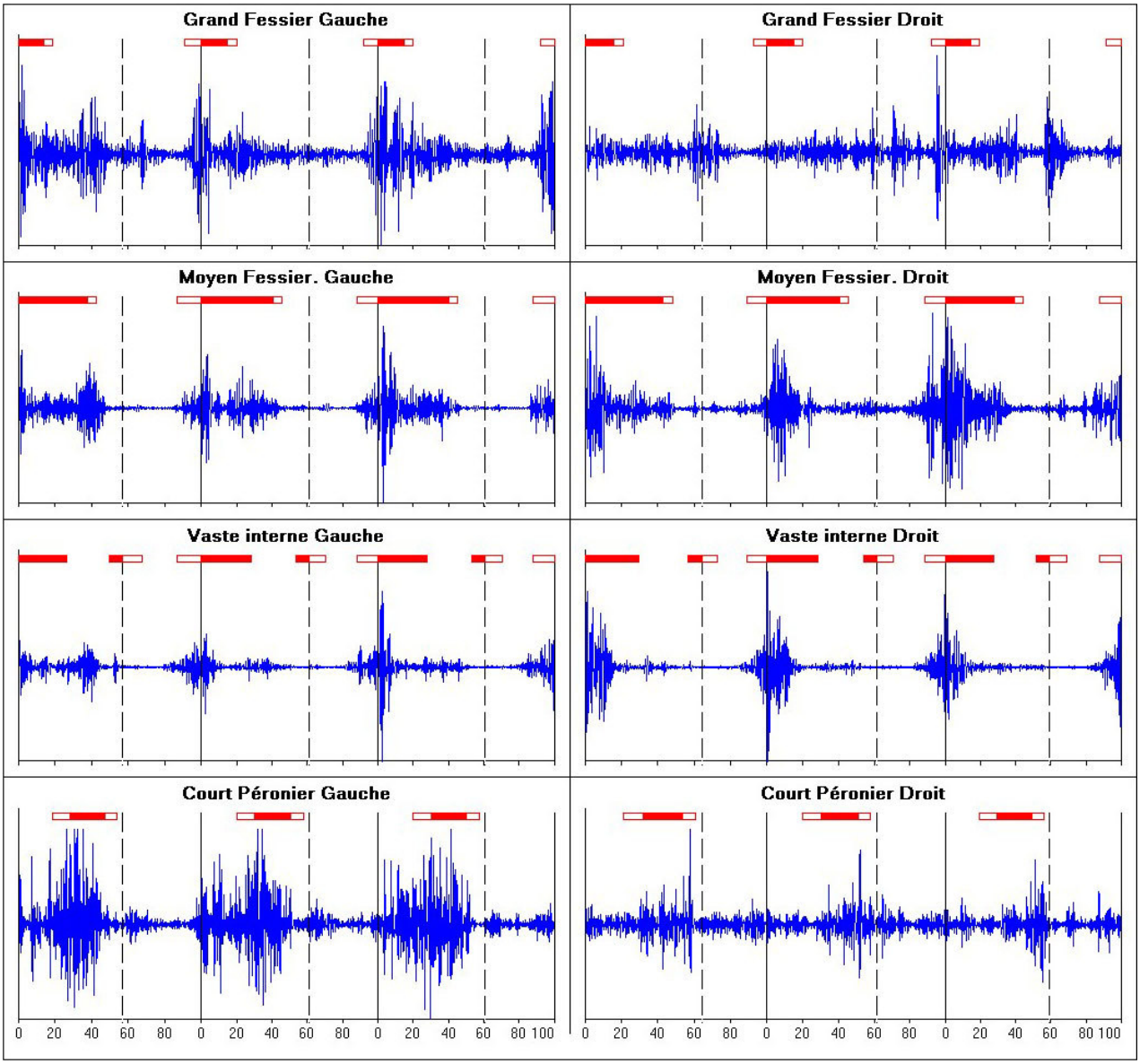


03/02/2004


Cycle retenu : CINEMATIQUE
03/02/2004
Gauche
Normal
Droit
Antéversion Bassin
Post/Ant (°)
Obliquité Bassin
Bas/Haut (°)
Rotation Bassin
Ext/Int (°)
Flex/Ext Hanche
Ext/Flex (°)
Abd/Add Hanche
Abd/Add (°)
Rotation Hanche
Ext/Int (°)
Flex/Ext Genou
Ext/Flex (°)
Var/Val Genou
Val/Var (°)
Rotation Genou
Ext/Int (°)
Plant/Dors Cheville
Pla/Dor (°)
Progression Pied
Ext/Int (°)
Rotation Cheville
Ext/Int (°)
Cycle de marche (%)

Paramètres électromyographiques sur plusieurs cycles de marche




Grand Fessier Gauche
Grand Fessier Droit
Moyen Fessier. Gauche
Moyen Fessier. Droit
Vaste interne Gauche
Vaste interne Droit
Court Péronier Gauche
Court Péronier Droit
0 20 40 60 80 0 20 40 60 80 0 20 40 60 80 100
0 20 40 60 80 0 20 40 60 80 0 20 40 60 80 100

Enfant X

Né le 18/09/1993 age : 11a5m

IMC Hémiplégie G, Prématurité 36SA PN =2880
Pied creux varus équin
ILMI et inégalité de longueur des pieds

Td = 137 cm
Ta = 69 cm
Poids = 24,5 kg

	Dt	G	Largeurs
MbInf (EIAS/MI)	72	71	Bassin : 16,5 cm
			Genou : 8,5 / 8,3
Quadriceps (5) :	26	26	Chevilles : 6 / 5,5
Mollets :	25	23,5	
Pieds (longueur)	22	20,5	

BILAN ARTICULAIRE

DROIT	EXAMEN	GAUCHE
Flex/Ext//Abd/Add//RE/RI 140/+10//45/35//40/50	Hanches	Flex/Ext//Abd/Add//RE/RI 140/+10//45/35//35/55
30	Antéversion Fémorale Clinique	35
20	Torsion tibiale externe	15
160/ +5	Genoux	160/ +5
0	Angle mort	0
0 mm	Rotule	0 mm
+25 / +35 50	Chevilles FD FP	+5 /+20 50
Valgus =10	Arrière pieds (valgus/Varus)	Varus = 5
- - - - - - -	Médio-pied pied creux Cavus Métatarsus varus Supinationavant-pied Hallux valgus Griffes	- + + - - 5 -

BILAN SPASTICITE [V3/V1 (Echelle d'Ashworth)]

MEMBRES INFERIEURS

DROIT	EXAMEN	GAUCHE
-	Adducteurs courts (hanches et genoux fléchis)	-
-	Adducteurs longs (hanches et genoux étendus)	-
-	Rotateurs externes	-
-	Rotateurs internes	-
-	Ischio-jambiers « poplité »	+20 / +40 A2
-	Ischio-jambiers « Lasègue »	30°
-	Triceps total (genoux étendus)	-20 / +5 A3
-	Soléaires (genoux fléchis)	-5 / +20 A2
-	Droit antérieur (en décubitus ventral)	+20 / +50 A2
-	Ely Test	+/- à 110°

BILAN MUSCULAIRE

DROIT	EXAMEN	GAUCHE
5	Psoas	5
5	Grand fessier	5
5	Moyen fessier	5
5	Quadriceps	5
5	Ischio-jambiers internes	5
5	Biceps	5
5	Jambiers antérieurs	4
5	Péroniers	4
5	Triceps	4
5	Jambiers postérieurs	4
5	Extenseurs communs orteils	4
5	Extenseurs propre GO	4
5	Fléchisseurs communs orteils	4
5	Fléchisseurs propres GO	4

-	Flexum hanches direct	-
10	Flexum hanches avec droit antérieur	15
-	Flexum genoux	-
5	Recurvatum passif des genoux	5
-	Equin	10

Léger steppage G à la marche

Annexe C

Echelles cliniques et patrons d'activité EMG

C.1 Echelle d'Ashworth modifiée

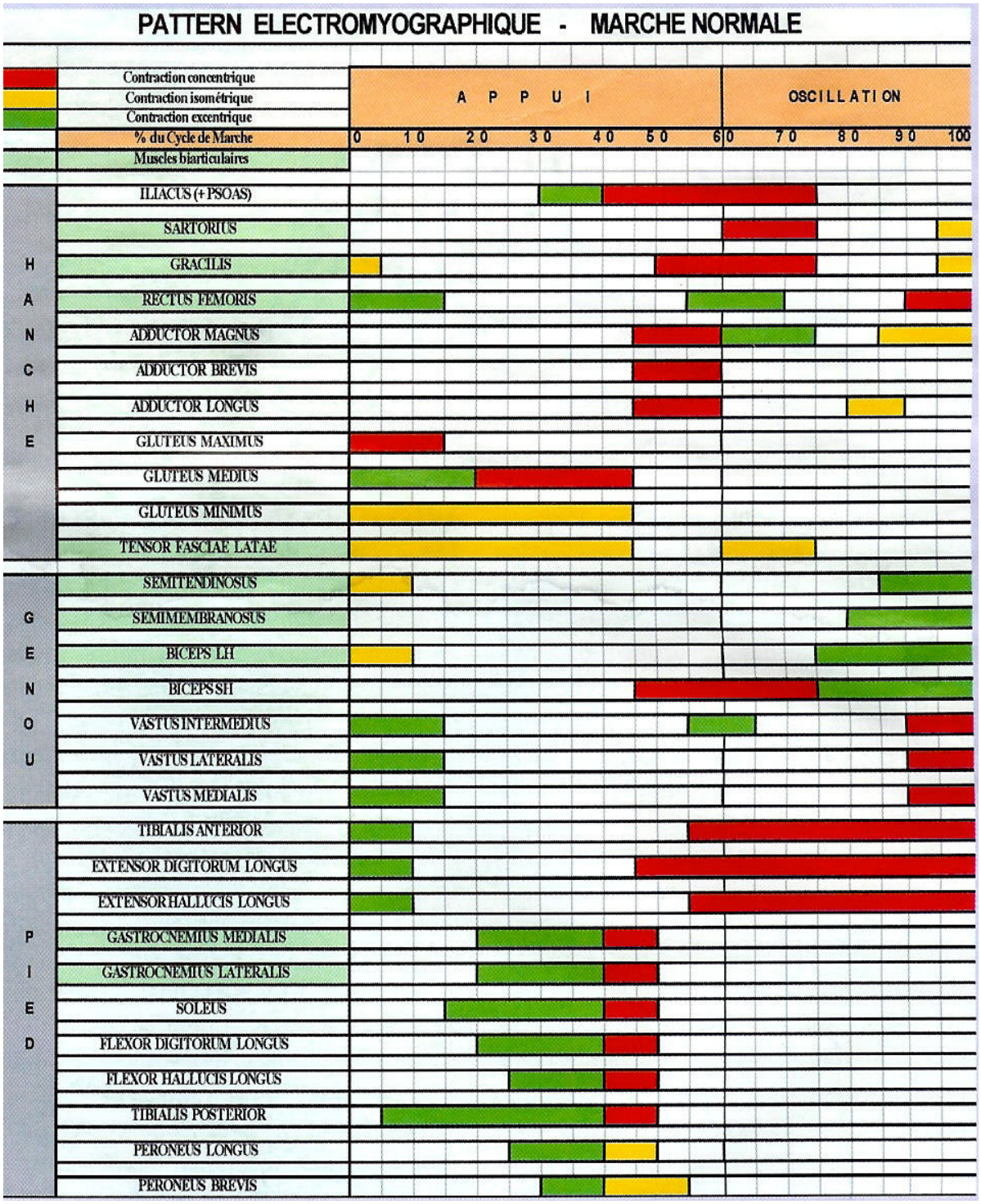
Les mobilisations passives sont réalisées à vitesse V2 (V2 étant la vitesse de la pesanteur)

Score	Description
0	Pas d'augmentation du tonus
1	Légère augmentation du tonus, avec un ressaut à la mobilisation passive suivie d'un relâchement ou une résistance minime en fin d'amplitude
1+	Légère augmentation du tonus, manifestée par un ressaut suivie d'une résistance minimale sur le reste (moins de la moitié) de l'amplitude
2	Hypertonie plus marquée sur la quasi-totalité de l'amplitude, mais mobilisation passive réalisée facilement
3	Hypertonie très importante ; mobilisation passive difficile
4	Contracture musculaire invincible ou clonus inépuisable

C.2 Cotation de la force musculaire pour un test manuel

Score	Description
0	Aucune contraction
1	Contraction perceptible sans mouvement
2	Mouvement complet sans pesanteur
3	Mouvement complet contre la pesanteur
4	Mouvement complet contre une résistance faible
5	Force musculaire normale – Mouvement complet contre une résistance élevée.

C.3 Patrons d'activité électromyographique pendant la marche normale (Filipetti, 2003)



Annexe D

Base de Règles

Liste des abréviations utilisées dans la base de règles :

En-tête du tableau : p-valeur de vérité de la règle, nb. ind.-nombre d'individus de l'ensemble d'apprentissage utilisé pour créer la règle.
Mesure clinique : SPA-Spasticité, FOR-Force, AdM-Amplitude de Mouvement.
Articulation : Chev-Cheville, Gen-Genou, Han-Hanche.
Muscle : Quad-Quadriceps, Ischio-Jamb--Ischio-Jambier, Jamb. Ant.-Jambier Antérieur.
Modalité linguistique : Faib-Faible, Moy-Moyen, Imp-Important.
Mouvement : Flex-Flexion, Ext-Extension.

Règles du groupe 1

	Groupe	p	nb. Ind.	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5	Condition 6	Condition 7	Condition 8	Condition 9
R1-1	G1	1.00	22	SPA Triceps Faib.	FOR Quad. Moy.							
R1-2	G1	1.00	3	SPA Triceps Faib.	FOR Quad. Imp.	AdM Ext. Chev. Faib.						
R1-3	G1	0.95	8	SPA Triceps Faib.	AdM Ext. Chev. Moy.							
R1-4	G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Faib.						
R1-5	G1	0.97	9	SPA Triceps Faib.	FOR Jamb. Ant. Moy.							
R1-6	G1	1.00	2	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Moy.	SPA Quad. Imp.					
R1-7	G1	0.77	4	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Moy.	SPA Quad. Moy.					
R1-8	G1	1.00	2	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Imp.	SPA Ischio-Jamb. Faib.					
R1-9	G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Moy.	SPA Quad. Moy.	AdM Ext. Han. Imp.				
R1-10	G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Imp.	SPA Ischio-Jamb. Moy.	FOR Jamb. Ant. Moy.				
R1-11	G1	1.00	3	SPA Triceps Faib.	FOR Quad. Imp.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	AdM Ext. Gen. Faib.	AdM Flex. Gen. Imp.			
R1-12	G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Moy.	SPA Quad. Imp.	FOR Jamb. Ant. Moy.	AdM Flex. Han. Moy.			
R1-13	G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Moy.	SPA Quad. Moy.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Faib.		
R1-14	G1	0.80	1	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Moy.	AdM Ext. Han. Moy.	FOR Triceps Moy.	AdM Ext. Chev. Faib.			
R1-15	G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Imp.	SPA Ischio-Jamb. Moy.	FOR Jamb. Ant. Imp.	AdM Flex. Chev. Imp.	SPA Quad. Faib.	AdM Flex. Gen. Imp.	
R1-16	NON-G1	0.73	43	SPA Triceps Imp.								
R1-17	NON-G1	0.82	14	SPA Triceps Moy.	AdM Ext. Gen. Moy.							
R1-18	NON-G1	0.86	5	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Imp.						
R1-19	NON-G1	0.88	3	AdM Ext. Gen. Imp.	AdM Ext. Han. Moy.	SPA Quad. Faib.						
R1-20	NON-G1	0.81	9	FOR Quad. Imp.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	AdM Ext. Gen. Moy.					
R1-21	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Moy.	SPA Quad. Imp.	FOR Jamb. Ant. Imp.				
R1-22	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Imp.	SPA Ischio-Jamb. Imp.	AdM Flex. Chev. Moy.				
R1-23	NON-G1	1.00	1	SPA Triceps Faib.	FOR Quad. Imp.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	AdM Ext. Gen. Faib.	AdM Flex. Gen. Faib.			
R1-24	NON-G1	0.86	1	AdM Ext. Gen. Faib.	SPA Quad. Moy.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.					
R1-25	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Imp.	SPA Ischio-Jamb. Moy.	FOR Jamb. Ant. Imp.	AdM Flex. Chev. Moy.			
R1-26	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Moy.	SPA Quad. Imp.	FOR Jamb. Ant. Moy.	AdM Flex. Han. Imp.	FOR Triceps Imp.		
R1-27	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Imp.	AdM Ext. Han. Imp.	SPA Ischio-Jamb. Moy.	FOR Jamb. Ant. Imp.	AdM Flex. Chev. Imp.	SPA Quad. Moy.		
R1-28	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Moy.	SPA Quad. Moy.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Imp.	AdM Flex. Gen. Moy.	
R1-29	NON-G1	1.00	1	SPA Triceps Moy.	AdM Ext. Gen. Faib.	FOR Ischio-Jamb. Moy.	SPA Quad. Moy.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Moy.	AdM Ext. Chev. Imp.	Diff. Long. jambe Moy.

Règles du groupe 2

Règle	Groupe	p	nb. Ind.	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5	Condition 6
R2-1	G2	0.78	6	SPA Triceps Imp.	AdM Flex. Chev. Faib.	SPA Quad. Moy.			
R2-2	G2	1.00	4	SPA Triceps Imp.	AdM Flex. Chev. Faib.	SPA Quad. Imp.			
R2-3	G2	0.75	5	SPA Triceps Imp.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Faib.	FOR Jamb. Ant. Moy.	AdM Ext. Chev. Moy.	
R2-4	G2	1.00	2	SPA Triceps Imp.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Faib.	FOR Jamb. Ant. Imp.	SPA Quad. Faib.	
R2-5	G2	1.00	1	SPA Triceps Imp.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Faib.	FOR Jamb. Ant. Moy.	AdM Ext. Chev. Imp.	SPA Quad. Imp.
R2-6	NON-G2	0.91	29	SPA Triceps Faib.					
R2-7	NON-G2	0.76	33	SPA Triceps Moy.					
R2-8	NON-G2	0.82	24	AdM Flex. Chev. Imp.					
R2-9	NON-G2	0.91	2	AdM Flex. Chev. Faib.	SPA Quad. Faib.				
R2-10	NON-G2	0.79	5	AdM Flex. Chev. Moy.	AdM Ext. Gen. Moy.				
R2-11	NON-G2	0.85	6	SPA Triceps Imp.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Imp.			
R2-12	NON-G2	1.00	1	SPA Triceps Imp.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Faib.	FOR Jamb. Ant. Faib.		
R2-13	NON-G2	0.86	4	AdM Flex. Chev. Moy.	FOR Jamb. Ant. Imp.	SPA Quad. Moy.			
R2-14	NON-G2	1.00	1	SPA Triceps Imp.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Faib.	FOR Jamb. Ant. Imp.	SPA Quad. Imp.	
R2-15	NON-G2	0.82	3	AdM Ext. Gen. Faib.	FOR Jamb. Ant. Moy.	AdM Ext. Chev. Imp.	SPA Quad. Moy.		

Règles du groupe 3

Règle	Groupe	p	nb. Ind.	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5	Condition 6	Condition 7	Condition 8	Condition 9	Condition 10	Condition 11
R3-1	G3	0.75	4	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Moy.	SPA Quad. Moy.	AdM Flex. Han. Imp.							
R3-2	G3	0.76	15	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Moy.	AdM Flex. Gen. Imp.						
R3-3	G3	1.00	13	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Moy.	SPA Quad. Moy.	AdM Flex. Han. Imp.	AdM Ext. Gen. Imp.						
R3-4	G3	0.70	2	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Imp.	AdM Ext. Chev. Imp.	SPA Quad. Moy.						
R3-5	G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Imp.	AdM Ext. Chev. Imp.	SPA Quad. Imp.						
R3-6	G3	0.81	5	SPA Ischio-Jamb. Imp.	AdM Ext. Gen. Moy.	AdM Ext. Chev. Moy.								
R3-7	G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Imp.	AdM Ext. Chev. Imp.	SPA Quad. Faib.	AdM Flex. Gen. Moy.					
R3-8	G3	0.73	2	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Imp.	AdM Flex. Han. Imp.	AdM Ext. Gen. Faib.					
R3-9	G3	0.82	1	SPA Ischio-Jamb. Moy.	AdM Ext. Han. Moy.	SPA Quad. Moy.	FOR Triceps Moy.	AdM Flex. Gen. Imp.	AdM Ext. Gen. Faib.					
R3-10	G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Moy.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	SPA Triceps Moy.				
R3-11	G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Imp.	AdM Flex. Han. Imp.	AdM Ext. Gen. Imp.	SPA Quad. Imp.				
R3-12	G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Moy.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	SPA Triceps Imp.	SPA Quad. Moy.			
R3-13	G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Moy.	SPA Quad. Moy.	FOR Triceps Moy.	AdM Flex. Gen. Imp.	AdM Ext. Gen. Imp.	Diff. Long. jambe Faib.	FOR Jamb. Ant. Moy.	SPA Triceps Imp.	
R3-14	NON-G3	0.82	30	SPA Ischio-Jamb. Faib.										
R3-15	NON-G3	1.00	2	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Faib.									
R3-16	NON-G3	0.81	6	AdM Ext. Han. Faib.										
R3-17	NON-G3	0.82	7	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Imp.									
R3-18	NON-G3	0.77	4	SPA Quad. Faib.										
R3-19	NON-G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Moy.	SPA Quad. Imp.								
R3-20	NON-G3	0.92	4	AdM Flex. Chev. Faib.										
R3-21	NON-G3	0.89	3	SPA Ischio-Jamb. Moy.	AdM Ext. Han. Moy.	SPA Quad. Faib.								
R3-22	NON-G3	0.75	3	SPA Ischio-Jamb. Moy.	AdM Ext. Han. Moy.	SPA Quad. Imp.								
R3-23	NON-G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Imp.	AdM Ext. Chev. Moy.							
R3-24	NON-G3	0.80	6	AdM Flex. Chev. Moy.	AdM Ext. Gen. Faib.									
R3-25	NON-G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Imp.							
R3-26	NON-G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Faib.							
R3-27	NON-G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Moy.	SPA Quad. Moy.	FOR Triceps Faib.						
R3-28	NON-G3	0.78	5	SPA Ischio-Jamb. Moy.	AdM Ext. Han. Moy.	SPA Quad. Moy.	AdM Flex. Gen. Moy.							
R3-29	NON-G3	0.83	3	SPA Quad. Faib.	AdM Flex. Gen. Imp.									
R3-30	NON-G3	0.77	4	AdM Flex. Chev. Moy.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Moy.								
R3-31	NON-G3	0.78	2	AdM Flex. Han. Imp.	SPA Quad. Faib.									
R3-32	NON-G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Imp.	FOR Triceps Imp.	AdM Flex. Han. Imp.	AdM Ext. Gen. Imp.	SPA Quad. Moy.				
R3-33	NON-G3	0.75	3	SPA Ischio-Jamb. Moy.	SPA Quad. Moy.	FOR Triceps Moy.	AdM Flex. Gen. Imp.	AdM Ext. Gen. Moy.	SPA Triceps Moy.					
R3-34	NON-G3	1.00	2	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Moy.	SPA Quad. Moy.	FOR Triceps Moy.	AdM Flex. Gen. Imp.	AdM Ext. Gen. Moy.	SPA Triceps Imp.			
R3-35	NON-G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Moy.	SPA Quad. Moy.	FOR Triceps Moy.	AdM Flex. Gen. Imp.	AdM Ext. Gen. Imp.	Diff. Long. jambe Moy.			
R3-36	NON-G3	1.00	1	SPA Ischio-Jamb. Moy.	AdM Flex. Chev. Imp.	AdM Ext. Han. Moy.	SPA Quad. Moy.	FOR Triceps Moy.	AdM Flex. Gen. Imp.	AdM Ext. Gen. Imp.	Diff. Long. jambe Faib.	FOR Jamb. Ant. Imp.		
R3-37	NON-G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Moy.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	SPA Triceps Imp.	SPA Quad. Imp.	Diff. Long. jambe Moy.		
R3-38	NON-G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Moy.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	SPA Triceps Imp.	SPA Quad. Imp.	Diff. Long. jambe Faib.	AdM Flex. Han. Moy.	
R3-39	NON-G3	1.00	1	SPA Ischio-Jamb. Imp.	AdM Ext. Han. Moy.	AdM Flex. Chev. Moy.	AdM Ext. Gen. Moy.	AdM Ext. Chev. Imp.	FOR Jamb. Ant. Imp.	SPA Triceps Imp.	SPA Quad. Imp.	Diff. Long. jambe Faib.	AdM Flex. Han. Imp.	FOR Ischio-Jamb. Moy.

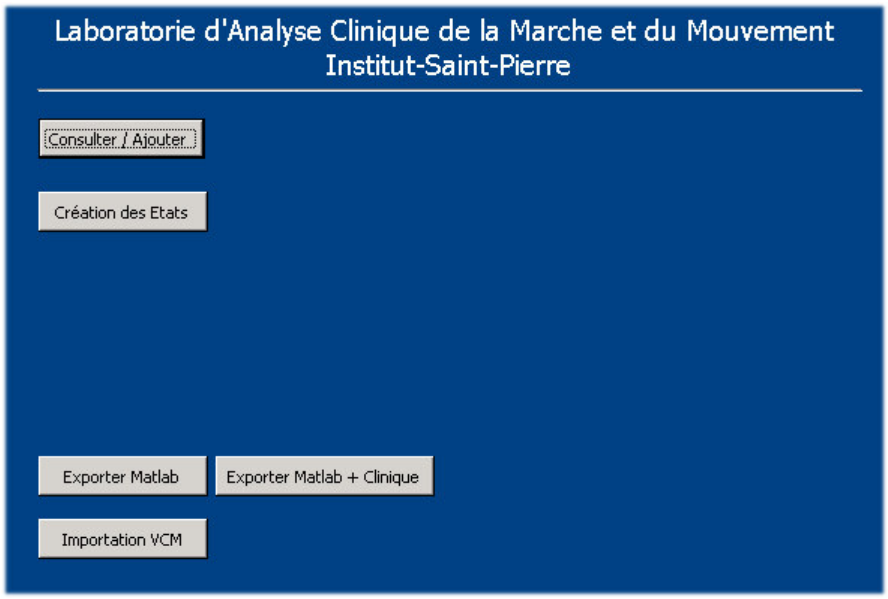
Annexe E

Présentation des interfaces graphiques

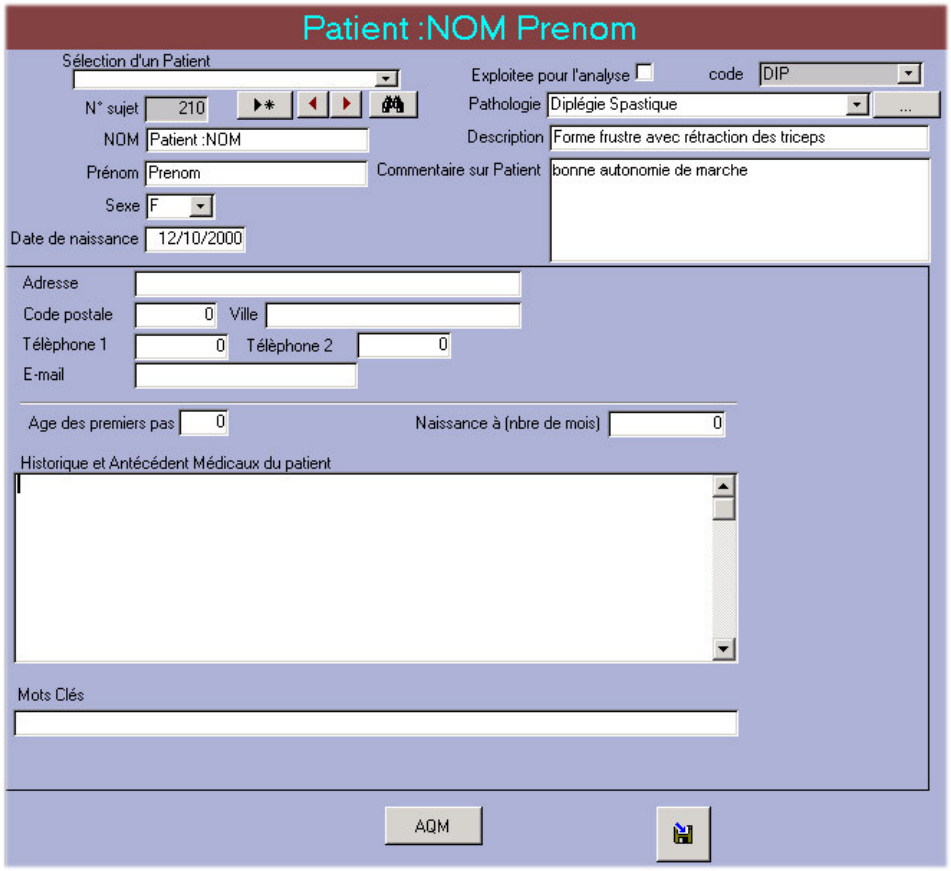
Deux interfaces ont été réalisées dans le cadre de ce travail de thèse. Elles sont utilisées au laboratoire d'analyse de la marche de l'Institut Saint Pierre. La première interface concerne l'acquisition des données relatives aux patients et à l'AQM, elle a été développée avec Access. La seconde concerne le calcul et l'affichage des résultats, elle a été développée avec Matlab.

E.1 Interface graphique créée avec Access :

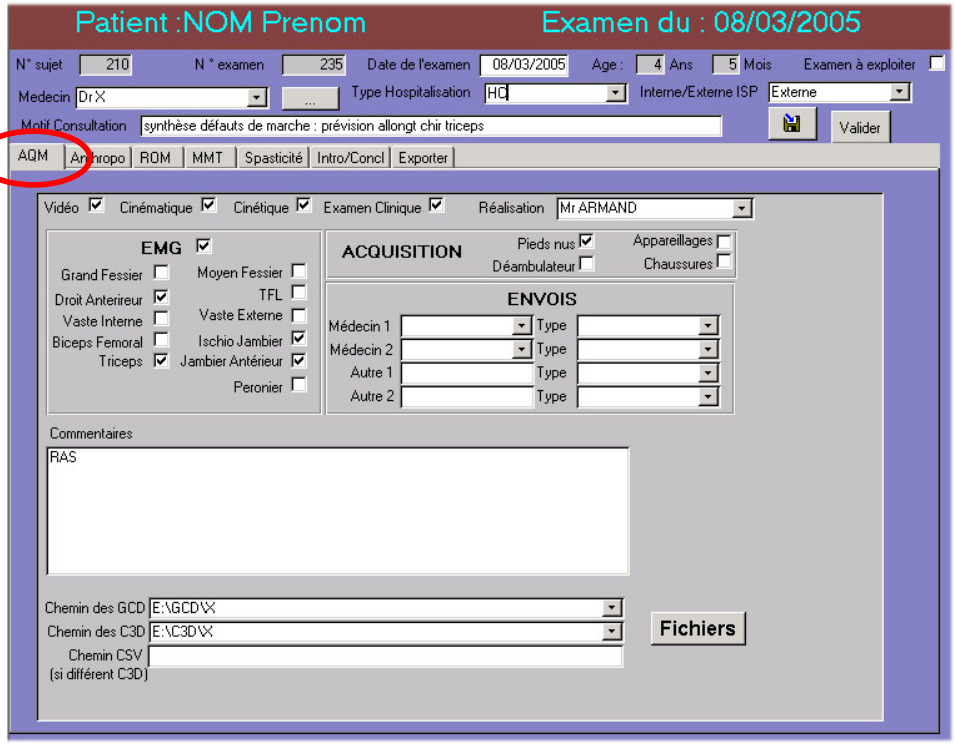
La première fenêtre donne accès à différents modules permettant de consulter ou ajouter des enregistrements, de créer de états (comme la liste des examens réalisés entre deux dates), permet d'exporter les données vers matlab (avec ou sans les données cliniques) et de récupérer les données du logiciel VCM (comme les chemins des fichiers de données brutes et calculées ainsi que les paramètres spatio-temporaux : contact du pied avec le sol, lever du pied….).
Seule la partie permettant de consulter et ajouter des enregistrements est présentée.



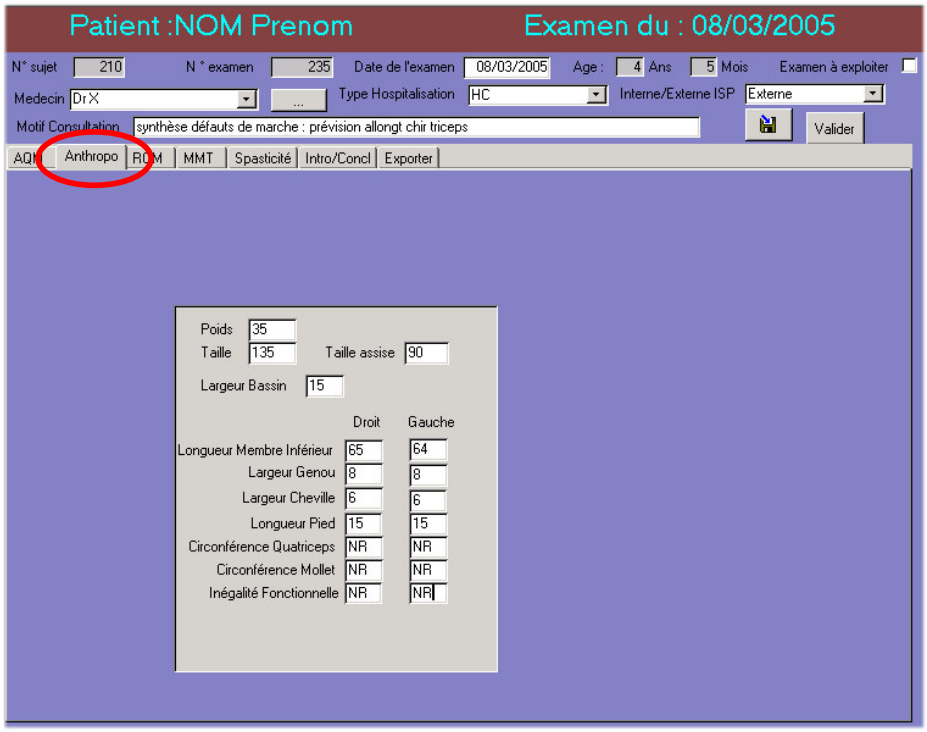
Cette fenêtre permet d'entrer les données spécifiques à un patient et à sa pathologie. Le bouton AQM donne accès aux fenêtres suivantes.



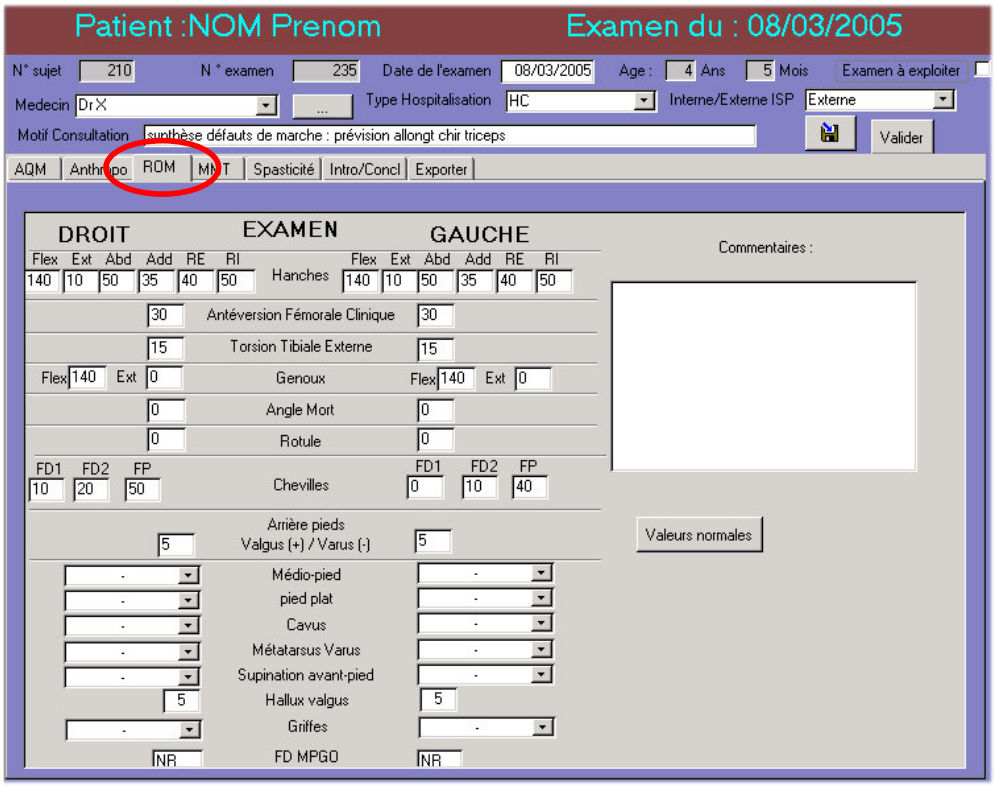
Fenêtre correspondant aux données de l'AQM



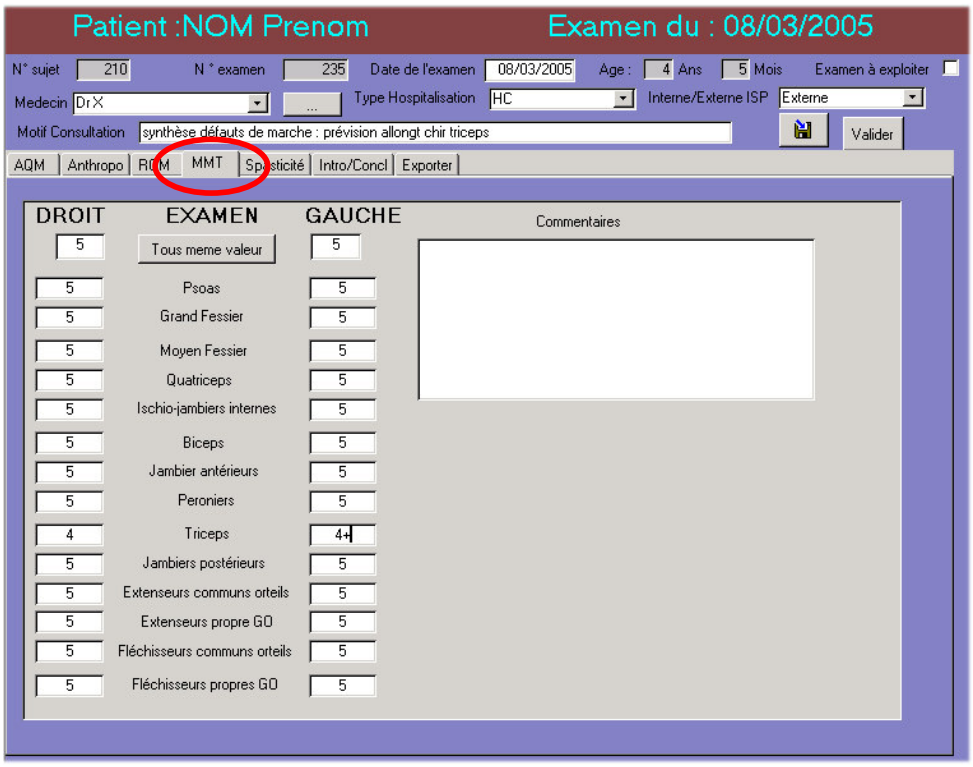
Fenêtre correspondant aux données anthropométriques du patient



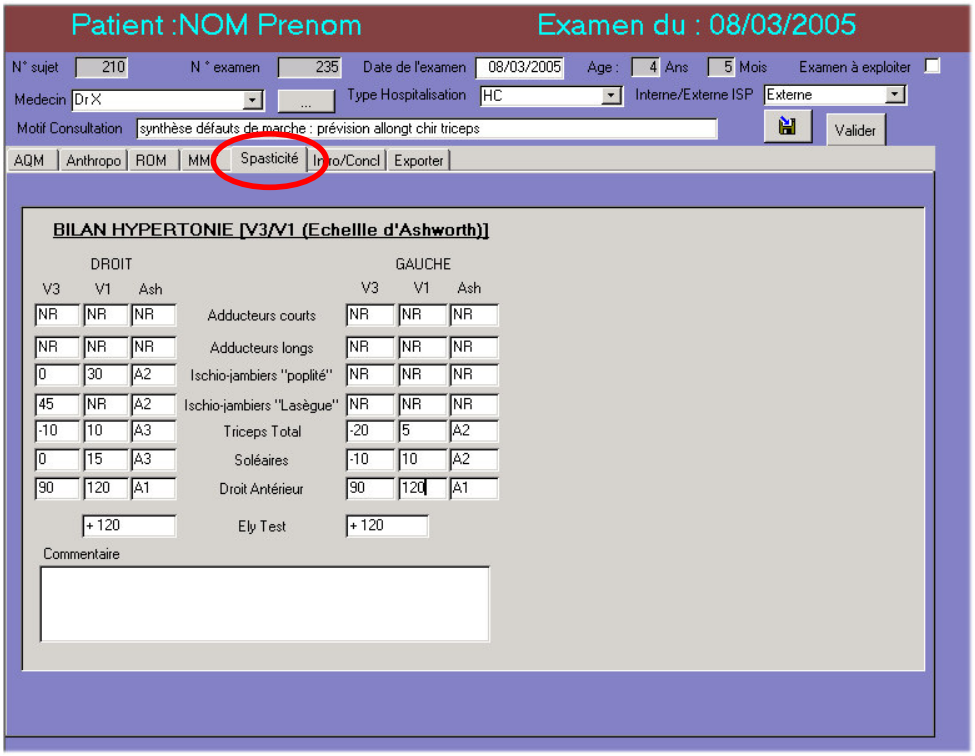
Fenêtre correspondant à l'évaluation des amplitudes articulaires



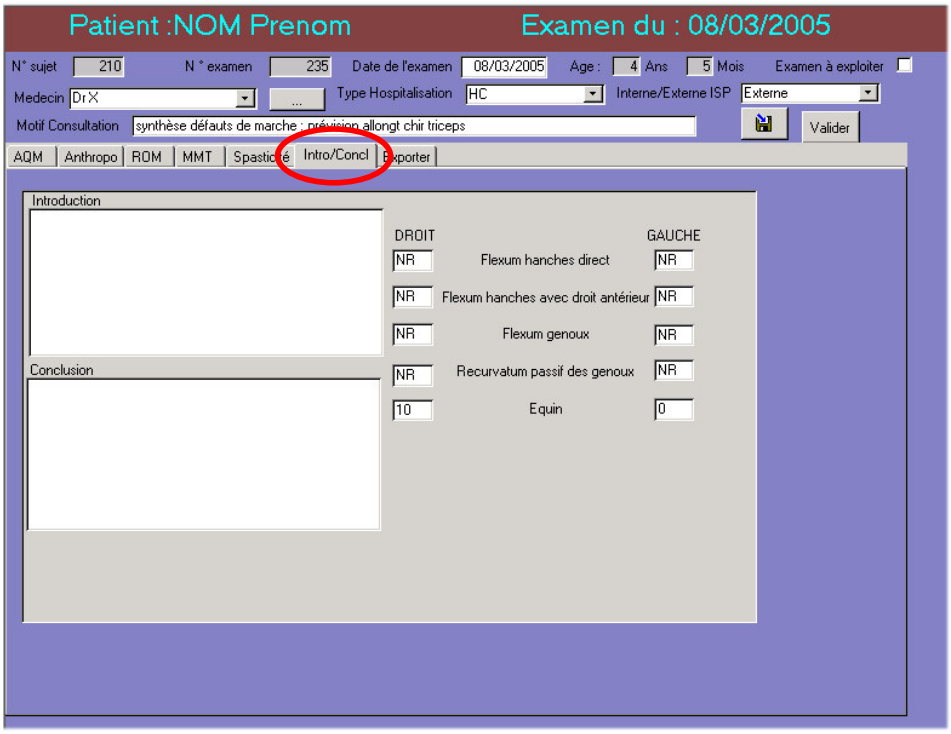
Fenêtre correspondant à l'évaluation de la force musculaire



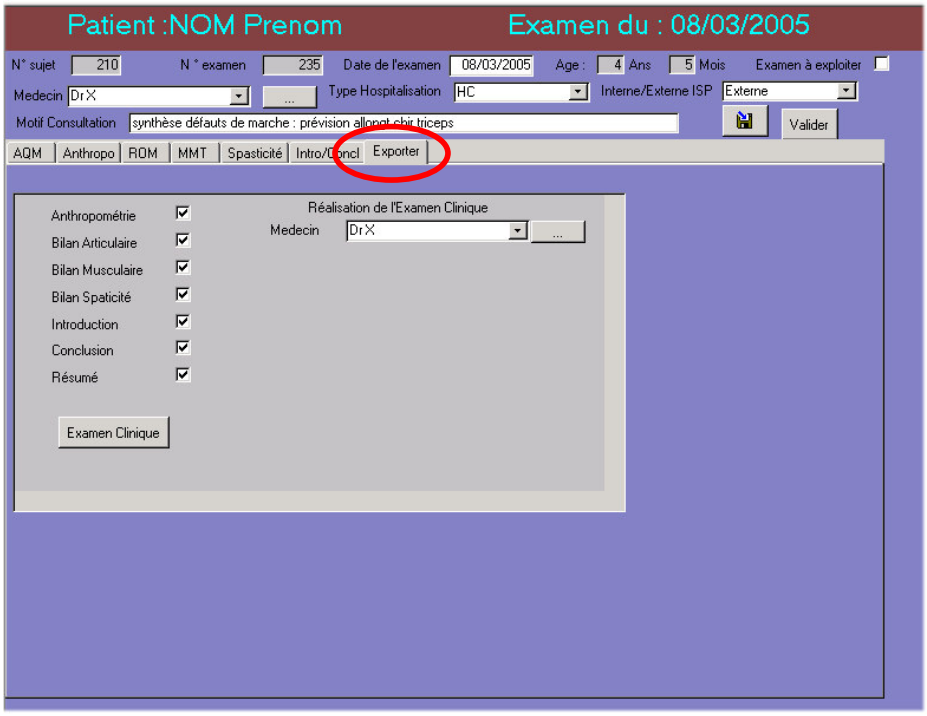
Fenêtre correspondant à l'évaluation de la spasticité



Fenêtre permettant d'entrer des informations libres et les informations importantes du bilan articulaire



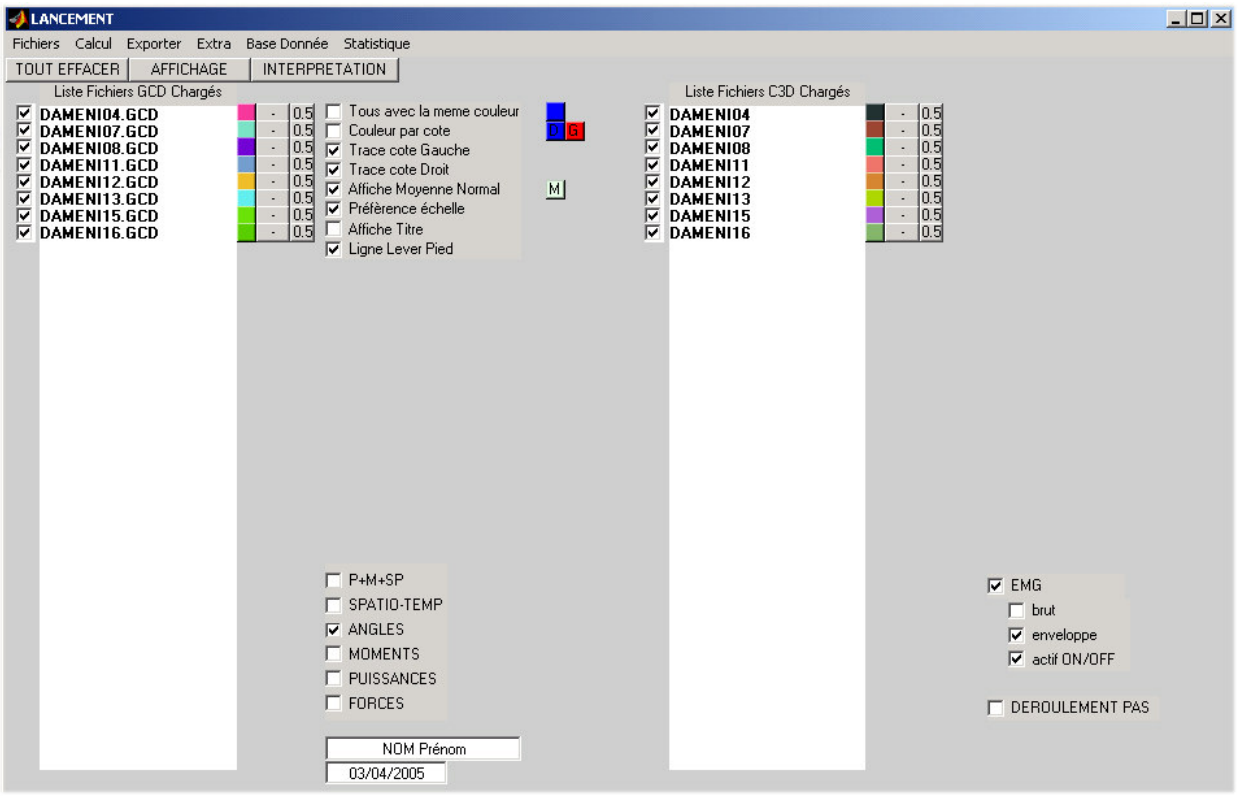
Fenêtre permettant de choisir les éléments qui seront exportés pour la création d'un document PDF.



E.2 Interface développée avec Matlab

Cette interface a été développée pour le calcul et l'affichage des résultats. La figure représentée correspond à une utilisation où les données d'un patient sont chargées pour créer le rapport de l'AQM (comme celui présenté dans l'Annexe B).

A gauche, apparaît la liste des fichiers GCD chargés, ces fichiers comprennent les données calculées par le logiciel VCM (cinématique et cinétique). A droite, apparaît la liste des fichiers C3D chargés, ces fichiers comprennent les données brutes fournies par le logiciel Workstation (Oxford Metrics Inc.) (coordonnées des marqueurs, forces de réaction au sol, activité électromyographique). Pour chaque fichier, correspondant chacun à un passage, il est possible de choisir la couleur, l'épaisseur et le style de trait. D'autres options sont également disponibles pour l'affichage. En bas, chaque "*checkbox*" correspond à un affichage des variables de la marche qui sont définies par l'utilisateur. Le résultat correspond à l'exemple type du rapport de l'AQM présenté dans l'Annexe B. Différents menus ont été créés pour faire des calculs (moyenne, angle spécifique, codage en fenêtres spatio-temporelles flous, codage de Benedetti (Benedetti *et al.* 1998), importer des données de la base de données (Access), exporter des données ou encore effectuer une analyse statistique.



Annexe F

Articles

Ce travail a donné lieu à deux articles soumis à une revue internationale indexée : Gait & Posture (facteur d'impact : 1.585).

Ces articles correspondent respectivement à une partie des études présentées dans les chapitres III et IV.

Le premier article : "Identification and classification of toe-walkers based on ankle kinematics, using a data-mining method" est **sous-presse**. Il est disponible en ligne sur le site de science direct

Le second article : " Mapping the clinical measurements and gait patterns of toe-walking using fuzzy decision trees" est **revisé et soumis** depuis le 28 Septembre 2005.

DTD 5

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Identification and classification of toe-walkers based on ankle kinematics, using a data-mining method

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Abstract

A database of 1736 patients and 2511 gait analyses was reviewed to identify for trials where the first rocker was absent. A fuzzy c-means algorithm was used to identify sagittal ankle kinematic patterns and three groups were identified. The first showed a progressive dorsiflexion during the stance phase, while the second had a short-lived dorsiflexion, followed by a progressive plantarflexion. The third group exhibited a double bump pattern, moving successively from a short-lived dorsiflexion to a short-lived plantarflexion and then returning to a further short- lived dorsiflexion before ending with plantarflexion until toe-off. The three patterns were linked to different neurological conditions. Myopathy, neuropathy and arthogryposis essentially revealed group 1 patterns, whereas idiopathic toe-walkers mainly displayed group 2 patterns. Cerebral palsy patients, however, were relatively homogeneously distributed amongst the three groups. Able-bodied subjects walking on their toes showed a high proportion of unclassifiable ankle patterns, due to a variable gait whilst toe walking. Despite the variety of neurological conditions included in this meta-analysis repeatable biomechanical patterns appeared that could influence therapeutic management.

Keywords: Gait analysis; Biomechanics; Data-mining; Toe-walking; Fuzzy c-means

1. Introduction

Toe-walking has been defined as the failure of the heel to make contact with the floor at the onset of stance [1] or as an absence of a heel rocker. In normal gait, the term ''heel rocker'' corresponds to the progression of the limb while the heel is the pivotal area of support [2]. The rear of the foot contacts the floor and rolls into plantarflexion. Without a heel rocker phase, either the mid- or forefoot touches the floor, or the ankle moves toward dorsiflexion.

Toe-walking is a very common gait deviation in children and is considered normal up until three years old [3]. It is also associated with cerebral palsy (CP) [4–10], muscular dystrophy [11–13], neuropathy [14] and in bony deformities such as clubfoot [15]. In the absence of any known cause, idiopathic toe walking (ITW) is the term used to describe the toe–toe gait pattern.

Toe-walking studies usually have one of three major aims. Firstly researchers have tried to distinguish between toe-walker groups, especially between idiopathic toe-walkers and children with mild cerebral palsy [5–8,16]. Fifteen years ago, Hicks et al. [8] identified different causes for toe-walking in CP and ITW: for CP, the cause was excessive knee flexion whereas for ITW, toe-walking was due to plantarflexion. More recently, Kelly et al. [7] pointed out characteristic patterns of knee and ankle motion that differentiated the two pathologies. Kalen et al. [16] found no

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differences between ITW and CP patients in their study using electromyography; however, Rose et al. [5] has since shown that electromyography of functional exercises can help to distinguish between CP and ITW. Secondly researchers have attempted to understand the biomechanical consequences of toe walking. For Kerrigan et al. [17], toe walking may require less ankle plantarflexor, ankle dorsiflexor, and knee extensor strength than normal heel–toe walking, and thus may have compensatory advantages for patients with upper motor neuron injury and weakness in the distal lower extremities. On the contrary, Perry et al. [1] concluded that toe-walking demanded more effort than heel–toe walking, given a higher electromyographic activity in the triceps surae. Thirdly some researchers have sought to distinguish the primary and secondary gait deviations of cerebral palsy [9] by comparing able-bodied subjects walking voluntarily on their toes with CP toe-walkers, although this subject appears to have received less attention in the literature given the paucity of references. All of these studies focus on a particular aspect of toe-walking, either pathological or biomechanical.

Considerable debate concerns treatment choices for toe-walking, especially in children with cerebral palsy [18–21], but also in idiopathic toe-walkers [22] or patients suffering from myopathy [12]. Understanding the causes of toe-walking clearly aids the optimisation of treatment plans; for example, distinguishing between dynamic tightness and fixed contracture [10,23] in cerebral palsy patients has allowed improvement in management [21].

Multidimensional data analysis, particularly cluster analysis, has been used successfully to identify gait patterns in normal walking [24], to classify gait deviations in children with cerebral palsy [25], to distinguish gait patterns in elderly men [26], to classify patients with arthrodesis compared to able-bodied subjects [27], and to monitor progress of gait patterns after a stroke [28]. Unlike the classic clustering methods, the fuzzy c-means clustering method used by Su et al. [27] has the advantage of not assigning a patient strictly to a well-defined group, but rather determines group membership based on all the clusters considered. This method permits the patients most characteristic of each group to be highlighted, the patients in the same group to be compared, and the evolution of a specific patient's gait to be monitored via several post- intervention and/or post treatment evaluations. Thus, the fuzzy c-means clustering method would appear to be appropriate for distinguishing between toe-walking gait patterns. Our purpose was three-fold: firstly to select all toe- walkers from an extensive database and define the proportions of this gait deviation; secondly to research potential patterns in the ankle sagittal kinematics of toe- walkers, and thirdly to link these patterns to differing neurological conditions.

2. Method

2.1. Subjects and database

The entire database of the gait analysis laboratory of the Institut Saint-Pierre was reviewed for toe-walkers. From 1993 to 2003, 1736 patients underwent 2511 gait analysis examinations for various reasons: to evaluate gait before and/or after an intervention, to monitor gait progression or to analyse gait problems. This database seems to be representative of patients examined in a gait lab. From one to eight gait analysis examinations were performed per patient. This study examined 11,950 trials. Fig. 1 sum- marizes the number of patients per disease. Diseases accounting for less than 10 patients (e.g. poliomyelitis and Marfan's syndrome) or patients displaying symptoms not attributable to a specific disease were classed under 'various'. The patient database included 982 boys and754 girls, with a mean age of 13.7 8.4 years.

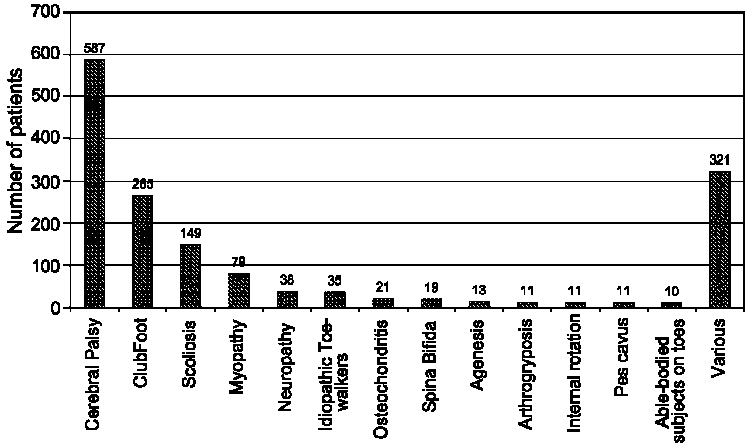

Fig. 1. Number of patients per disease.

2.2. Gait analysis procedure

Gait acquisition comprised a three-dimensional (3D) analysis with a minimum of three trials for each session, including synchronous kinematic, kinetic, and bilateral electromyography (EMG) recordings of the lower limb. A biomechanical engineer oversaw all analyses. A five-camera motion analysis system (Vicon® VX replaced by a Vicon® 512 in 1999, Oxford Metrics, UK) and two force platforms (AMTI®, USA) embedded in the walkway were used. Markers placement was according to Davis's protocol [29], and the subjects walked the length (12 m) of the laboratory barefoot and at their usual speed. Spatio-temporal parameters, joint angle motion, internal joint moments and powers were computed using Vicon Clinical Manager (VCM, Vicon®, Oxford Metrics, UK).

2.3. Data processing

In this study, toe walking was defined by the absence of a heel rocker. Gait trials with flat–foot and fore–foot initial contacts were included; only trials with a heel–foot initial contact were excluded. The slope of the sagittal ankle kinematics during the first nine percent of the gait cycle, corresponding to the first rocker [2,30], was used to select those trials presenting toe-walking. The slope S of the ankle kinematic was calculated during the stance phase: $S = DA/Dt$ with A as ankle kinematics and t as time. Without a first rocker, there was no movement towards plantarflexion and the ankle kinematics showed a permanent movement toward dorsiflexion. The entire VCM database was loaded with Access (Microsoft Corporation), which was linked to Matlab (The MathWorks, USA) for all the data processing.

Exclusion criteria were defined on several levels: for patients if all sessions from a patient were incomplete, for sessions if a patient was older than 20 years old to keep a homogeneous population, a session with fewer than three selected trials, for trials if extreme outliers for the selected trials were excluded with the subsequent method. For each angle and for each slope value, the threshold was defined as the first quartile minus three times the interquartile range and the third quartile plus three times the interquartile range [31].

During stance phase, the slope of the ankle kinematics resampled on 30 points was coded as "1" if the curve went upwards (towards dorsiflexion, thus a positive slope), and "0" if the curve went downwards (towards plantarflexion, thus a negative slope) or if the slope value was nil. To identify patterns in the ankle kinematic data, the fuzzy c-means algorithm (FCM) was used with the following parameters: a fuzzification exponent, $m = 2$; a minimal improvement, $e = 10^{-5}$; and a maximal number of iterations $t = 100$. The input of FCM was the sequences of 0–1 for all the trials selected and the output was the trials membership values to clusters. This clustering method, which allows one piece of data to belong to two or more clusters, was developed by Dunn in 1973 [32] and improved by Bezdek in 1981 [33]. FCM is frequently used in pattern recognition, particularly for the image processing used in MRIs. Su et al. [27] have used FCM to identify gait patterns in arthrodesis patients and describe the method in detail. To determine the number of clusters, the FCM was processed from 2 to 10 clusters and the partition coefficient [33]—which measures the fuzziness of the partition—was used to determine the optimum number of clusters. The optimum was defined when the partition coefficient reached its maximum. The mean of the trial membership values for each pattern was used to analyse the links with the diseases and ankle gait patterns identified. A session was assigned to one of the three groups if the mean membership was higher than 0.5. This criterion was made to avoid classifying an irreproducible session or a different pattern from those identified.

Angles, internal moments and powers in the sagittal plane were reported for each ankle pattern. The mean was weighted by the trials membership values to characterize each ankle pattern. Means were taken over trials that had a membership value superior to 0.5. Partly suggested by Benedetti et al. [34] and Kerrigan et al. [17], the gait parameters found in Table 1 correspond to the local kinematic and kinetic maximum or minimum for curves representing ankle, knee and hip movements in the sagittal plane as well as spatio-temporal parameters. One-way variance analysis (ANOVA) was used to examine the effect of the identified group on gait parameters at an a level of 0.01. All significant ANOVA tests were followed by Tukey's honestly significant difference test for unequal sizes (Spjotvoll-Stoline test) for multiple comparisons in order to determine significant differences at an a level of 0.01. All statistical analysis was done using Statistica for Windows 6.0 (Statsoft, France).

3. Results

The research algorithm run on the entire database identified 10426 trials with no first rocker, 5188 for the right side and 5238 for the left side. After eliminating the outliers, the selected trials corresponded to 41% of 2287 sessions with 1570 patients under 20 years old, 54% for both sides, 20% for only the left and 26% for only the right. The percentages of toe-walkers in each disease category are presented in Fig. 2. These percentages are over 50% for four of the diseases and the control group: cerebral palsy (62%), myopathy (51%), idiopathic toe-walking (83%), arthrogryposis (65%) and able-bodied children walking on their toes (100%). The percentages drop under 50% for the other diseases: neuropathy (44%), clubfoot (29%), spina bifida (18%), gait with internal rotation (17%) and pes cavus (20%). Only two diseases presented a proportion of toe-walkers under 10%: scoliosis (6%) and agenesis (3%).

The partition coefficient was used to determine the number of toe-walker clusters; in this case, there was a

Table 1
Mean and standard deviation of angles, moments and power peaks charted in Fig. 3 and spatio-temporal parameters

Code	Variable	Type	Parameter	Phase	Unit	Group 1		Group 2		Group 3		Statistical difference		
						Mean	S.D.	Mean	S.D.	Mean	S.D.	G1 vs. G2	G1 vs. G3	G2 vs. G3
HR1	Pelvis	Angle	Mean	AC	°	14.59	7.64	16.07	7.79	15.98	7.25	*	–	–
H1	Hip	Angle	Value	IC	°	39.15	9.91	42.69	11.44	43.23	9.35	*	*	–
H2	Hip	Angle	Max. Ext.	AC	°	1.14	11.83	0.76	13.13	0.04	9.31	–	–	–
H3	Hip	Angle	Max. Flex.	SwP	°	43.02	9.92	46.06	11.30	46.68	9.60	*	*	–
K1	Knee	Angle	Value	IC	°	22.17	14.52	31.92	17.53	33.16	12.90	*	*	–
K2	Knee	Angle	Max. Flex.	LR	°	27.70	13.68	35.80	15.73	35.53	11.77	*	*	–
K3	Knee	Angle	Max. Ext.	MS	°	15.85	14.98	17.12	18.76	16.22	13.17	–	–	–
K4	Knee	Angle	Max. Flex.	SwP	°	60.14	10.58	62.43	10.28	59.78	8.81	*	–	*
A1	Ankle	Angle	Value	IC	°	4.68	10.21	6.40	10.39	5.23	10.31	*	–	–
A2	Ankle	Angle	Max. Dorsi.	LR	°	5.46	9.16	5.76	9.91	6.69	9.76	–	–	–
A3	Ankle	Angle	Max. Dorsi.	AC	°	14.21	9.82	5.98	9.99	7.49	9.82	*	*	–
A4	Ankle	Angle	Max. Plantar.	SwP	°	9.72	12.26	21.82	13.40	15.62	12.87	*	*	*
A5	Foot progression	Angle	Mean	AC	°	8.90	14.62	0.91	15.50	0.62	11.54	*	*	–
MH1	Hip	Moment	Max. Ext.	LR	N m/kg	0.83	0.41	0.87	0.44	1.03	0.51	–	*	*
MH2	Hip	Moment	Max. Flex.	MS	N m/kg	0.76	0.29	0.82	0.28	0.82	0.30	*	*	–
MH3	Hip	Moment	Max. Ext.	SwP	N m/kg	0.39	0.16	0.46	0.18	0.49	0.19	*	*	–
MK1	Knee	Moment	Max. Flex.	LR	N m/kg	0.27	0.22	0.22	0.25	0.18	0.23	*	*	–
MK2	Knee	Moment	Max. Ext.	LR	N m/kg	0.40	0.34	0.46	0.46	0.52	0.43	–	*	–
MK3	Knee	Moment	Max. Flex.	MS	N m/kg	0.09	0.23	0.04	0.30	0.21	0.28	*	*	*
KM4	Knee	Moment	Max. Ext.	TS	N m/kg	0.34	0.26	0.43	0.38	0.45	0.31	*	*	–
MA1	Ankle	Moment	Max. Ext.	LR	N m/kg	0.77	0.29	1.25	0.32	1.26	0.37	*	*	–
MA2	Ankle	Moment	Max. Ext.	TS	N m/kg	1.14	0.29	0.99	0.29	1.11	0.30	*	–	*
PH1	Hip	Power	Max. Gen.	LR	W/kg	0.58	0.60	0.81	0.66	1.03	0.74	*	*	*
PH2	Hip	Power	Max. Abs.	MS	W/kg	0.83	0.45	0.99	0.45	0.97	0.50	*	*	–
PH3	Hip	Power	Max. Gen.	SwP	W/kg	0.62	0.44	0.81	0.56	0.87	0.60	*	*	–
PK1	Knee	Power	Max. Gen.	StP	W/kg	0.32	0.44	0.42	0.64	0.75	0.73	–	*	*
PK2	Knee	Power	Max. Abs.	StP	W/kg	0.58	0.52	0.64	0.50	0.67	0.57	–	–	–
PA1	Ankle	Power	Max. Abs.	LR	W/kg	0.43	0.39	1.57	0.87	1.60	0.88	*	*	–
PA2	Ankle	Power	Max. Gen.	MS	W/kg	0.08	0.19	0.84	0.48	0.80	0.56	*	*	–
PA3	Ankle	Power	Max. Abs.	MS	W/kg	0.40	0.28	0.20	0.31	0.48	0.35	*	–	*
PA4	Ankle	Power	Max. Gen.	TS	W/kg	1.45	0.92	1.31	0.91	1.33	0.66	*	*	–
T1	Stance phase				%GC	63.50	5.00	62.22	4.20	63.38	3.79	*	–	*
T2	Swing phase				%GC	36.50	5.00	37.78	4.20	36.62	3.79	*	–	*
T3	Stride length				cm	91.81	20.50	92.04	17.56	93.97	16.65	–	–	–
T4	Stride time				S	1.06	0.18	0.93	0.14	0.95	0.12	*	*	–
T5	Cadence				stride/s	0.96	0.16	1.10	0.16	1.07	0.14	*	*	*
T6	Speed				cm/s	88.99	23.99	100.61	20.08	99.61	17.37	*	*	–

Max.: maximum; Min.: minimum; Flex.: flexion; Ext.: extension; S.D.: standard deviation; AC: all cycles; StP: stance phase; SwP: swing phase; IC: initial contact; LR: loading response; MS: mid-stance; TS: terminal stance; Gen.: generation; Abs.: absorption; GC: gait cycle.
* Significant at $p < 0.01$.

maximum for three groups. Fig. 3c presents the three groups of toe-walkers based on the pattern of the ankle kinematics during the stance phase, as identified by fuzzy c-means clustering. The first group (G1) showed a long and progressive dorsiflexion, followed by plantarflexion until toe-off. The second group (G2) presented a short-lived dorsiflexion, followed by a progressive plantarflexion until toe-off. The third group (G3) exhibited a double bump pattern, moving successively from a short-lived dorsiflexion (as in the second group), to a short-lived plantarflexion, back to a short-lived dorsiflexion and ending with a plantarflexion until toe-off.

Forty-four percent (633) of the sessions (with each side considered independently) belonged to G1, 19% (268) belonged to G2, 16% (232) belonged to G3 and 21% had a mean membership under 0.5. Over 50% of those with clubfoot, scoliosis, myopathy, neuropathy, osteochondritis, spina bifida and arthrogryposis fell into group G1. A high percentage of idiopathic toe-walkers (44%) belonged to G2. Cerebral palsy patients were more evenly spread through the three groups: 36% in G1, 23% in G3 and 19% in G2. A high percentage (45%) of the control sessions—able-bodied persons walking on their toes—presented a membership under 0.5, though 25% of the sessions could be classified as G2, 20% as G3, and 10% as G1 (see Fig. 4 for disease distributions by group).

Spatio-temporal parameters and the sagittal kinematics and kinetics of the ankle, knee and hip indicated significant differences between the groups (Table 1). Spatio-temporal results indicated a lower stance phase (T1) and consequently a higher swing phase (T2) for G2, compared to G1 and G3. Stride time (T4) and speed (T6) were lower for G1. Cadence

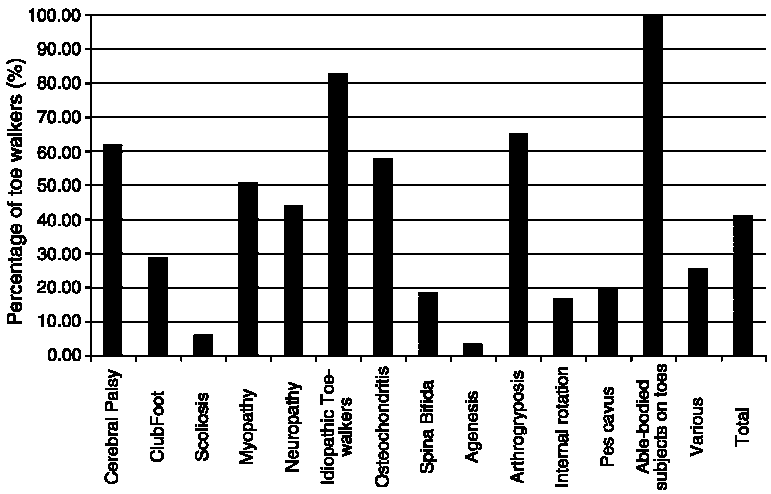

Fig. 2. Prevalence of toe-walking deviation in each disease.

(T5) was significantly different for the three groups. There was no difference in stride length (T3). The mean pelvic tilt (HR1) was slightly lower for G1 than it was for G2. Plantarflexion at initial contact (A1 in Fig. 3c) was slightly lower for G1, compared to G2. The maximal dorsiflexion in the loading response phase (A2) did not present significant differences. Maximal dorsiflexion (A3) was higher for G1 compared to G2 and G3. Maximum plantarflexion (A4) showed a significant difference in the three groups. The mean angle foot progression (A5) was quasi-neutral for G2 and G3, whereas G1 displayed an external angle. The internal moment at the ankle (MA1 in Fig. 3f) showed a higher peak during loading response for G2 and G3 in comparison with G1. This indicates that the application point of the ground reaction force remained in the forefoot, and certainly in the mid-foot for G1. The flexion moment in the terminal stance (MA2) showed higher values for G1 and G3 than G2. Ankle power (Fig. 3i) was different for the three groups. The energy absorption during loading response (PA1) and the energy generation (PA2) were higher for G2 and G3 compared to G1. In mid-stance, G1 and G3 presented absorption whereas G2 presented energy generation (PA3). Energy generation in terminal stance (PA4) had higher values in G1 compared to G2 and G3.

At the knee joint (Fig. 3b), flexion at initial contact (K1) and maximum flexion during loading response (K2) was higher for G2 and G3 compared to G1. Minimal flexion (K3) displayed no significant differences in mid-stance. Maximal flexion in the swing phase (K4) was slightly higher for G2 compared to G1 and G3. The internal extensor moment during loading response (MK2) showed higher values for G1 than G3. The flexor moment at initial contact (MK1) and the extensor moment in terminal stance (MK4) displayed lower values for G1 than for G2 and G3. There were significant differences in the extensor moment at mid-stance (MK3) for the three groups. In terms of power, the maximal energy generation (PK1) was higher for G3 than for the others, but there was no difference for the minimal energy generation (PK2).

At the hip joint (Fig. 3a), G1 presented a lower flexion at initial contact (H1) and in the swing phase (H3) than did G2 and G3. The minimal flexion in mid-stance (H2) presented no significant differences. G3 presented a higher extensor moment at initial contact (MH1). The maximal flexion moment in the stance phase (MH2) and the maximal extensor moment in the swing phase (MH3) were lower for G1 than for G2 and G3. In terms of moment, generation at initial contact (PH1) was significantly different for the three groups. The maximal absorption in stance phase (PH2) and the maximal generation at the end of the stance phase (PH3) showed lower values for G1 than for G2 and G3.

4. Discussion

Although fuzzy c-means has already been used in gait analysis [27], to our knowledge, data-mining—defined as extraction of knowledge in large databases—has not yet been used to characterize gait deviations. However, such scans of large databases has often been used in other medical fields, such as oncology and genetics [35,36]. Nonetheless, this data-mining method identified three toe-walking ankle patterns in a variety of diseases, and revealed that toe-walking is a major gait deviation (prevalence >50%) for patients with cerebral palsy, myopathy, arthrogryposis, as well as for idiopathic toe-walkers.

Many classifications exist in cerebral palsy, either based principally on the knee [37,38] or ankle position [4,25,39]. Group 3 of our study resembles the apparent equinus described by Rodda et al. [4], group IV described by Winters et al. [39], and the double bump ankle group of O'Byrne et al. [25]. Rodda et al. [4] thought the cause of toe-walking in apparent equinus was excessive flexion of the knee and

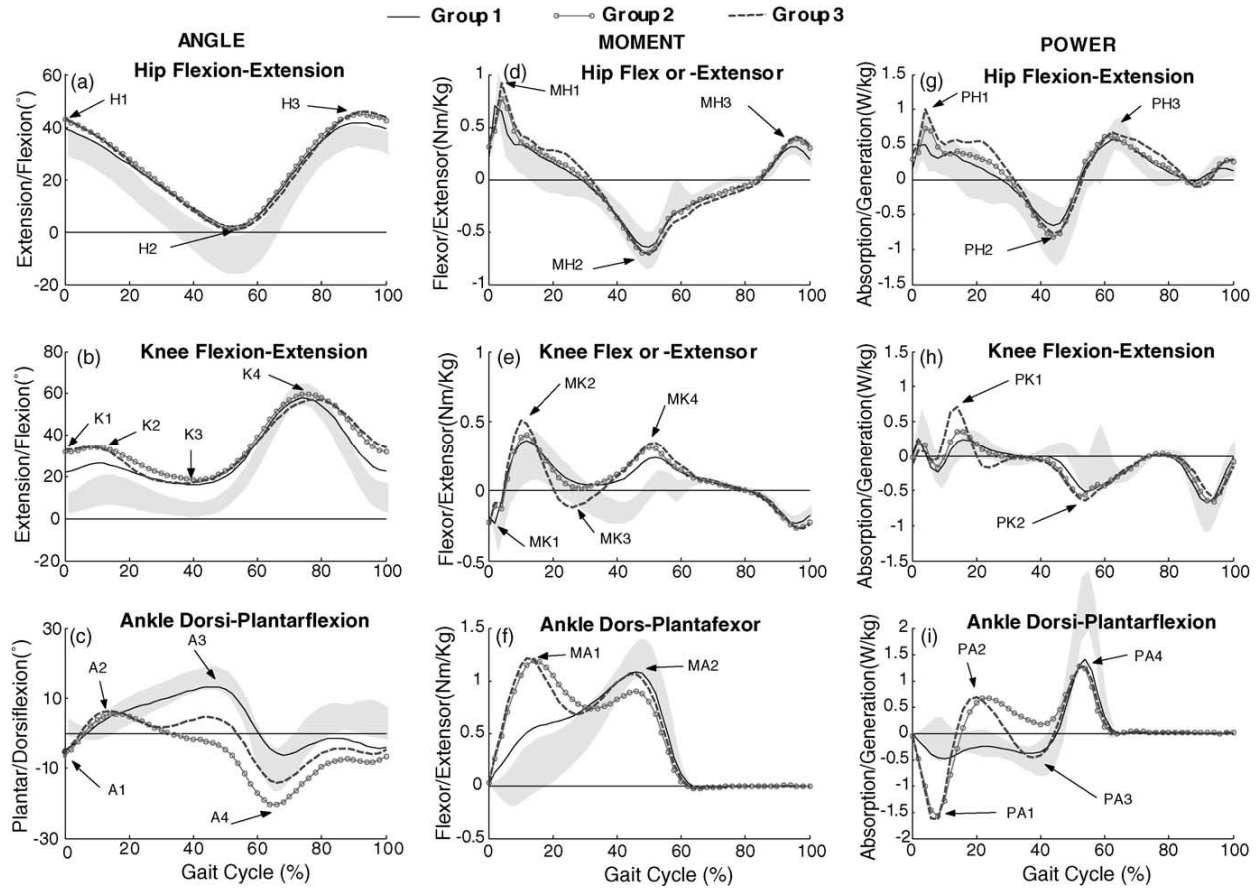

Fig. 3. Toe-walker joint angles (a–c), internal moments (d–f) and powers (g–i) in the sagittal plane for the ankle (c, f, i), for the knee (b, e, h) and for the hip (a, d, g). Mean 1 standard deviation forms the normal bandwidth (shadow) for normal subjects. Mean of the three patterns identified with the fuzzy c-mean algorithm are plotted with a black line for group 1, a light grey line marked with circles for group 2 and a dark grey dotted line for group 3. The characteristic curve instances referred to in the results are indicated with arrows.

hip. Our results also show excessive flexion at hip and knee for all three groups, although it was more substantial for groups 2 and 3. Such excessive flexion may be either the cause or the consequence of toe walking, and further investigations will be necessary to establish which it really is. Our group 2 corresponds to the true equinus and the jump gait of Rodda et al. [4] and to Winters' group III. Our group 1 is similar to Winters' group I and group II, and has the same pattern as the crouch gait of Rodda et al., only with more dorsiflexion.

Lin et al. [37] reported moments and powers according to cerebral palsy groups. Ankle plantarflexion moment values in our study gave groups 2 and 3 a double bump pattern, with higher values for group 3 at the end of the stance phase. The only pattern with a double bump in [37] was the jump gait. Our group 3 corresponds to Lin's jump group for power at the ankle, but none of Lin's groups resemble our group 2 with a permanent power generation at 40% of the gait cycle.

Idiopathic toe-walkers (35 subjects) were the most prevalent in our group 2. Hicks et al. [8] have reported an ankle pattern in idiopathic toe-walkers that is similar to our group 2 pattern, with a progressive plantarflexion in mid-stance. In addition, these authors described an ankle pattern in cerebral palsy that is close to our group 1 pattern. The low number of patients in the Hicks et al. study, seven per disease, could explain the fact that they only found a permanent dorsiflexion pattern in cerebral palsy.

There was a high prevalence of myopathic patients (79 subjects) in our group 1. Toe-walking in myopathy has been attributed to compensation for weakness in the quadriceps, fibrosis of the triceps surae and weakness in the tibialis anterior. A number of authors [11–13] have agreed that equinus increases progressively as the disease evolves. The ankle patterns described in these articles correspond to our group 1.

The gait of patients suffering from arthrogryposis has not, to our knowledge, been described in the literature. The arthogryoposis patients (11 subjects) were almost all members of our group 1. More investigations will be necessary to explain their complex gait, and patients often display little range of movement in each joint and a substantial external rotation of the lower limb. Toe walking could be

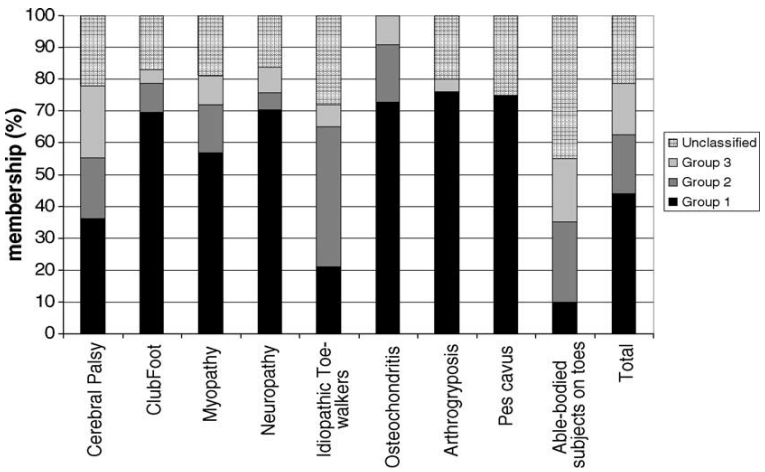

Fig. 4. Group membership per disease. The three groups were identified with a fuzzy c-means algorithm. The unclassified group corresponds to sessions presenting a mean membership inferior to 0.5. Diseases with less than 20% of toe-walkers (Fig. 2) were not reported.

explained by contracture of the triceps surae and fixed equinus associated with weakness in the tibialis anterior.

The gait linked to neuropathy has been described as fore–foot contact associated with premature activity in the triceps surae [14]. The fore–foot contact seems to increase the feeling of safety for those lacking physical self-assurance, such as the elderly [40]. Membership in group 1 was very high for patients suffering from neuropathy (38 subjects).

The proportion of unclassified sessions for able-bodied subjects walking on their toes (10 subjects) could be the consequence of an unreliable gait caused by able-bodied subjects not being used to walking on their toes. In a same session, sometimes a subject displayed pattern 2, and sometimes pattern 3. The mean ankle kinematics for able-bodied subjects on their toes reported by Davids et al. [9] are on the borderline of our groups 2 and 3. It is possible that some of the trials in this study corresponded to group 2 while others corresponded to group 3, with the mean of all trials resulting in the curve presented. However, Perry et al. [1] reported an ankle kinematic curve that corresponds to our group 3.

Interestingly, our group 2 had a pattern similar to the ankle pattern of stair ascent during the stance phase described by Riener et al. [41]. For these authors, forefoot contact during ascent permitted the ankle to be placed in a natural angular range. Idiopathic toe-walkers have been shown to display limited dorsiflexion [5,16], but their available range of passive dorsiflexion appears to exceed that of ambulation [42]. Research by Gordon et al. [43] has demonstrated that muscle tension depends on the degree of overlap between myosin and actin filaments. It is possible that toe walking during stair ascent, or in patients with short triceps surae, such as idiopathic toe-walkers, provides an angle range at the ankle corresponding to maximum force production in the sarcomere length–tension curve. In most cases, idiopathic toe-walkers and persons ascending stairs are able to strike the floor with the heel, but they choose forefoot contact instead. Such a choice could be also due to a more comfortable ankle position, with no relationship to the strength–length curve.

The following hypotheses could be offered to explain the links between our ankle patterns and clinical characteristics. In toe-walking cerebral palsy patients, Tardieu et al. [10] discerned two groups using the ratio between the passive moment and the total internal moment. The first group was characterized by an excessive contraction of the triceps surae muscle and the second group by a contracture of the tendon–muscle complex. Unfortunately, this article did not report ankle kinematics, but Tardieu's groups could correspond to our groups 2 and 3. Group 3 could be linked to excessive muscle activity and spasticity, and group 2 could be linked to contractures that are entirely, or at least partly, responsible for toe walking. Lack of a heel rocker in group 1 could be due to the weakness of dorsiflexor muscles [2]. Other toe-walking causes could be related to attempts to compensate for joint and muscle disorders above the ankle [10] or to the search for a compensatory advantage when walking [17].

Pattern identification could be a useful way to help make therapeutic choices. If group 2 corresponds to triceps surae stiffness caused by a fixed contracture, an intramuscular gastrosoleus lengthening might be appropriate [21]. If group 3 corresponds to triceps surae spasticity or "dynamic equinus", botulinum toxin injection or/and serial casts could have a positive effect [20]. If group 1 corresponds to weakness in dorsiflexor muscles or in the muscle above the ankle, it might be interesting to reinforce these muscles to decrease the progression of the weakness, thus allowing the gait to be maintained as long as possible [11], or to increase muscle strength, thus allowing a more comfortable gait.

This study has revealed some consistent biomechanical patterns but further investigations will be necessary to link the three group's gaits to their causes and clinical

examination. Electromyography could potentially be used for this. In the future it would be interesting to examine the relationship between the groups and the results of the different therapeutic treatments for various toe-walking patients.

5. Conclusion

Prevalence of toe walking in a large database confirmed that toe walking is a major gait deviation. Despite examining differing diseases, three major consistent ankle patterns emerged. Identification of clinical causes of these toe-walking patterns could improve gait analysis interpretation and influence therapeutic management. Some hypotheses of causes may explain our findings in part but they need to be tested in further studies.

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Mapping the clinical measurements and gait patterns of toe-walking using fuzzy decision trees

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Abstract
Toe-walking is one of the most prevalent gait deviations and has been linked to many diseases. Three major ankle kinematic patterns have been identified in toe-walkers, but the relationships between the causes of toe-walking and these patterns remain unknown. This study aims to identify these relationships. Clearly, such knowledge would help clinicians choose the best treatment plan for a patient exhibiting signs of toe-walking. Because the large quantity of data provided by gait analysis examination makes interpretation a difficult task, artificial intelligence techniques were used to facilitate interpretation as well as to decrease subjectivity. Of the 716 limbs evaluated, 240 showed signs of toe-walking and inclusion criteria. The ankle kinematic pattern of the evaluated limbs during gait was assigned to one of the three toe-walking pattern groups to build the training data set. Toe-walker clinical measurements (range of movement, muscle spasticity and muscle strength) were coded in fuzzy modalities, and fuzzy decision trees were induced to create intelligible rules allowing toe-walkers to be assigned to one of the three groups. A stratified ten-fold cross validation situated the classification accuracy at 81%. Twelve rules depicting the causes of toe-walking were selected, discussed and characterized using kinematic, kinetic and EMG charts. This study proposes an original approach to linking the possible causes of toe-walking with gait patterns.

Keywords : Gait analysis, clinical interpretation, biomechanics, fuzzy decision tree, toe-walking.

1 Introduction

Associated with many diseases, such as cerebral palsy, myopathy, and neuropathy [1], toe walking is a very common gait deviation that is defined as an absence of the first rocker. Three distinct kinematic ankle patterns (Figure 1) have been identified in the toe-walker gait for a large variety of diseases [1]. The first pattern shows progressive dorsiflexion during the stance phase, while the second presents a short dorsiflexion, followed by a progressive plantarflexion. The third group exhibits a double bump aspect, moving successively from a short dorsiflexion, to a short plantarflexion, returning to a short dorsiflexion and ending with a plantarflexion until toe-off [1]. These three gait patterns conformed to those identified in the literature [1].

The relationships between these patterns and the clinical causes of toe-walking have not been established in the literature, although Perry [2] does offer several possible causes of the lack of heel rocker: (a) pretibial muscle weakness, (b) inadequate tibialis anterior activity, (c) plantar flexion contracture, (d) soleus and gastrocnemius spasticity, (e) excessive voluntary ankle plantarflexion in compensation for quadriceps weakness, (f) knee flexion contracture caused by overactivity of the hamstring, and (g) combined spasticity of the hamstring and ankle plantarflexors. Toe walking can also be caused by a leg length discrepancy [3], a compensation for problems in the contralateral side [4], or a limited dorsiflexion due to calf muscle stiffness [5]. Most of these causes can be assessed by static examination including range of motion, spasticity, strength and anthropometric measurements [6].

However, all attempts to provide clinical explanations for toe-walking patterns have been obtained empirically and subjectively by means of expert interpretations. Linking patterns to causes is complicated by the fact that toe-walking is frequently not the result of a single clinical element, but rather of a combination of several elements, which makes it difficult to link any one pattern with specific gait deviations. Skaggs et al. [7] have shown a high degree of variability in gait analysis interpretations, which no doubt stems from this complexity. Still, given its potential impact on the treatment plan, identifying and interpreting the causes of gait deviations, such as toe-walking, remains an important task despite the difficulties. It would seem, then, that objectively identifying the relationships between the possible clinical causes of toe-walking by combining clinical measurements and the three kinematic ankle patterns would be a valuable addition to the existing body of knowledge. This knowledge could aid clinical practitioners in choosing the best treatment plan for a specific toe-walking patient.

Because identifying the causes of gait deviation is difficult using human reasoning alone, artificial intelligence techniques can be a helpful tool. For example, decision trees are often used in the medical fields to predict the class/group of a patient according to clinical characteristics [8]. Fuzzy decision trees (FDT) incorporate a notion of fuzziness that permits inaccuracy and uncertainty to be introduced and allow the phenomena under consideration to be expressed using natural language. Unlike "black box" neural networks or statistical approaches, FDT permit knowledge to be derived from data by providing an intelligible and interpretable input-output mapping. Since the “if-then” rules derived from FDT are easily intelligible, using FDT is a good way to deduce the potential causes of the three ankle gait patterns in toe-walking.

This article first evaluates the capacity of clinical measurements to predict ankle gait patterns. It then highlights the links between the possible causes of toe-walking and the three toe-walking ankle gait patterns. Finally, it provides a graphic representation of some typical toe-walker gaits in terms of their possible causes.

2 Method

2.1 Subjects

A total of 358 case studies of children, who had been evaluated via clinical examination and instrumented gait analysis from 2002 to 2004, were reviewed for this retrospective investigation. Both the examination and the analysis were performed by the same physical therapist and biomedical engineer. To be included in this study, the children had to meet the following selection criteria:

- absence of heel rocker, as assessed by instrumented gait analysis and video;
- have performed a minimum of three gait analysis trials;
- use no walking aids (cane, walker or orthopaedic device).

According to these criteria, 169 children (mean age 9.4±4.2 years), corresponding to 240 lower limbs, were selected to participate in the study.

2.2 Clinical assessment

Clinical examinations measured graded spasticity using the modified Ashworth scale [9]; passive range of motion of the hip, knee and ankle joints; and muscle strength according to a manual five-point scale [10]. Angular measurements were obtained using a handheld goniometer. Range of motion was tested using in gentle slow manoeuvres in order to avoid spastic muscle responses.

2.3 Gait Analysis

Gait analysis was performed using a five-camera motion measurement system (VICON 512; Oxford Metrics®, UK), two force plates (AMTI®, Watertown, USA) embedded in the experimental walkway, and a ten-channel Electromyography (EMG) system (MA-100, Motion-Lab®, USA). Reflective markers for video measurement were placed at defined anatomical points on the pelvis and lower limbs according to the Davis protocol [11]. Pre-amplified EMG surface electrodes were positioned according to SENIAM's recommendations [12]. Kinematic and kinetic parameters were calculated using the Vicon Clinical Manager software (Oxford Metrics®, UK), and Matlab (The MathWorks®, USA) was used to process the EMG envelopes. Electromyographic data were full-wave rectified and smoothed using a fourth-order Butterworth low-pass filter with a cut-off frequency of 10Hz [13], and then normalised for the signal amplitude. All patients were asked to walk at a self-selected speed along a 12-meter walkway. Under the direction of a biomechanical engineer, data were collected until five "clean" trials had been recorded for each child. Only trials in which the entire foot made contact with the force-plate without targeting were included in the analysis.

2.4 Classification method and rules extraction

2.4.1 Discrimination based on the subjective evaluation of gait analysis results and videos

The clinical examination measurements for each limb were coded using three normalized triangular fuzzy membership functions (also called fuzzy windows) related to the following three modalities: *Low, Average* and *High* (see Figure 2). Each fuzzy modality was defined by three parameters—a_i, b_i and c_i ($i \in \{1,2,3\}$)—where a_1 and c_3 tended to $-\infty$ and $+\infty$, respectively, and $a_2=b_1$, $a_3=b_2=c_1$ and $b_3=c_2$. Consequently, for this characterization of the variable range, only three parameters had to be defined for each clinical index: L_v, A_v, and H_v (see Figure 2). These parameters were determined based on the clinical measurements data distributions (L_v and H_v corresponding to the 5th and 95th percentiles, respectively, and A_v=median) and expert advice. Table 1 shows the parameters for each clinical measurement.

Let M_i^V be the fuzzy modality relative to the i^{th} fuzzy window of the variable V and defined by the parameters a_i, b_i and c_i. For an observed value x of a given variable V, the membership value $\mu_{M_i^V}(x)$ of the modality M_i^V is:

$$\mu_{M_i^V}(x) = \max\left(\min\left(\frac{x-a_i}{b_i-a_i}, 1, \frac{c_i-x}{c_i-b_i}\right), 0\right)$$

For example, for the variable *ankle plantarflexion*, $\{L_v, A_v, H_v\} = \{0, 30, 60\}$ (see Table 1), and a *plantarflexion* of 20 yields the following membership values: $\mu_{Low^{Plantarflexion}}(20)=1/3$, $\mu_{Average^{Plantarflexion}}(20)=2/3$ and $\mu_{High^{Plantarflexion}}(20)=0$.

2.4.3 Fuzzy decision tree and rules

Quinlan's Interactive Dichotomizer 3 (ID3) algorithm for decision tree induction was first described in 1986 [14,15]. Though several methods for adapting this algorithm to fuzzy data [16-18] have been proposed, all of them are based on the same principles. First, a learning set of observations (also called examples) is built. These set members are characterized both by their fuzzy membership values related to the modalities of a set of categorical variables (in our case, the clinical examination measurements) and by their fuzzy or crisp membership values related to the classes of a known category (in our case, the three toe-walking groups). This learning set is then subjected to a 4-step procedure:

1. A discriminating measure is used to determine which categorical variable best explains the distribution of the patients among the classes, and a node is created. (In this study, a discrimination measure based on information entropy was used (See Marsala [19] for more information))
2. The dataset is partitioned to build as many subsets as there are modalities for the variable chosen in step 1. (This study has three modalities per variable of the clinical examination measurements)
3. A termination condition is tested with the help of a termination criterion β. (The termination condition in this study is defined, for a given node level, with the conditional probability p of being in a class, given that the conjunction of fuzzy conditions from the "root" to the node is verified).
4. If the termination condition is verified, then the subset is considered to be a "leaf" of the tree. If the termination condition is not verified, then steps 1 to 3 are repeated.

In the present study, β was initially set at $\beta_0=0.7$, which seems to be a good compromise allowing the two antagonistic criteria, reliability and generality, to be managed.

Once the fuzzy decision tree has been created, each branch of the tree (i.e. the path from the root to the leaf of a fuzzy decision tree) can be converted into a rule. The rule ends at the leaf level, indicating the membership or the non-membership in the class for which the tree was induced. At the leaf level, *p* corresponds to the rule's fire strength. Each rule is then optimized according to the Yuan and Shaw method [16], by removing all fuzzy conditions that penalize the rule's fire strength.

Since the discrimination measure is particularly well adapted to two classes, as many trees are induced as there are classes, and each tree concludes with the membership or non-membership in a class. (The complete method was explained in detail by Marsala [19] and applied to biomechanical data by Roux [15] .) In our application, three FDT were induced, one for each of the three toe-walking groups. A rule that concludes in membership in a group is called a "yes" rule, and a rule that concludes in non-membership in a group is called a "no" rule.

2.4.4 Patient classification

In our study, the conditions of the rules are defined by the fuzzy characterization of the clinical measurements, and the conclusions indicate membership or non-membership in a toe-walking class. The fuzzy rules are, in fact, a sort of knowledge depository, with each rule containing a probable cause of toe-walking. Thus, this rule base can be used to objectively and automatically assign any given patient to the toe-walking class to which s/he probably belongs—which is precisely what we hoped to achieve. To test the accuracy, specificity and sensitivity of this rule-based classification system, a stratified ten-fold cross validation [15,20] was performed.

2.5 Rule illustration

A rule's premise—characterized by a combination of clinical measurements—provides an explanation of the membership of a class and thus constitutes a possible cause of a toe- walking pattern. Because several rules can conclude in the same ankle gait pattern, we felt it was important to illustrate how the different combinations of clinical measurements affected the other gait parameters (e.g. hip and knee kinematics, kinetics, EMG). Thus, patient gait analysis data were averaged according to membership weights (membership of a patient in a given rule), which produced a characteristic gait pattern (kinematics, kinetics for each joint and EMG) for each rule.

3 Results

3.1 Classification accuracy

Eighty-three rules (available as supplementary data on the gait and posture website) were obtained using the method described in the preceding section (2.4). The number of conditions per rule varied from 1 to 11, with an average of 4.2. The results of the stratified ten-fold cross validation are presented in Table 2 for each of the three patterns. Overall, our method was able to correctly classify toe-walkers most of the time, using the kinematic ankle patterns revealed by clinical examination, for a general accuracy rating of 81%. The general specificity rating was 84% and general sensitivity rating was 65%.

The percentages of toe-walkers correctly classified in relation to their disease are reported in Figure 3. Classification accuracy for idiopathic toe-walkers was less than 50%. The best results were for diseases presenting muscular weakness, such as myopathy or muscular spinal atrophy, yielding an accuracy rating of 100%.

3.2 Rule characterization

Table 3 summarizes the "yes" rules with no more than five conditions that were defined from tree branches whose leaves contained at least three examples of a given ankle pattern. The gait patterns associated with these 12 rules are presented in Figures 4, 5 and 6. In order to limit the discussion in this paper to the most important rules, the "yes" rules with more than 5 conditions and those that could classify either one or two ankle patterns were excluded from the discussion, as were any "no" rules. A classification performed on the learning set with only the 12 selected rules yielded 12 patients (10.4%) misclassified and 25 patients (17.2%) unclassified. The general accuracy with this reduced rule base was 72.4%.

All rules for group 1 (R1) correspond to low or average muscle spasticity in the triceps surae with some specific muscular weaknesses. The foot/floor angle at initial contact for identified patients (Figure 4d) was between -10° and 0°. The rules R1-1 and R1-4 concern toe-walking caused by muscular weakness: the first refers to quadriceps weakness and the second to tibialis anterior weakness. Patients classed according to these rules displayed no knee flexion in stance (Figure 4b), had plantarflexion at initial contact (Figure 4c) and a permanent flexor moment at the knee (Figure 4f), and exhibited average activity in the tibialis anterior at mid-stance (Figure 4o). In addition, patients with weakness in the quadriceps had no hip extension at the end of stance (Figure 4a). Patients identified by rules R1-2 and R1-3 had, respectively, a low and an average range of movement for plantarflexion. They displayed no plantarflexion in the swing phase (Figure 4c), and knee flexion was excessive at initial contact (Figure 4b). Patients designated by rule R1-2 exhibited an abnormal knee

extensor moment in mid-stance (Figure 4f). Rule R1-5 points to average spasticity in the triceps surae, with no noticeable characteristics showing up on the graphs.
Three rules from group 2 (R2) denote high spasticity in the triceps. Rules R2-1 and R2-2 indicate a limitation of dorsiflexion and average or high spasticity in the quadriceps. Patients designated by these rules displayed a high foot/floor angle at initial contact, between 25° and 35° (Figure 5d); a permanent knee flexion (Figure 5b) and hip flexion in stance (Figure 5a). They also exhibited a permanent knee extensor moment throughout the cycle (Figure 5f), a small ankle extensor moment in the end of the stance phase (Figure 5g), and a high ankle power absorption at initial contact (Figure 5k). The EMGs (Figures 5l,m,n,o) for these three rules were high for all the muscles at initial contact, and were relatively low at the terminal stance phase for the triceps surae, which is normally at its maximum at this point. Rule 2-3 indicates a significant limitation in knee extension. Patients designated by this rule exhibited a foot/floor angle near 10° at initial contact (Figure 5d), a high knee flexion (Figure 5b), a permanent knee extensor moment in the stance phase (Figure 5f), and a double bump pattern for the ankle extensor moment (Figure 5g), as well as a plantarflexion/dorsiflexion angle that hovered around 0° (Figure 5c).
Rules from group 3 (R3) indicate average or high spasticity in the hamstrings and a limited extension in either the ankle, knee or hip. All the patients classified using these rules exhibited a foot/floor angle between 0 and 10° at initial contact (Figure 6d), knee flexion at initial contact (Figure 6b) in conjunction with high hamstring spasticity, and correct knee extension in mid stance (Figure 6b), with one exception: those classified with rule R3-3 had an average limitation of knee extension.

4 Discussion

4.1 The originality of the method

This study focused on using FDT to classify the three toe-walking patterns obtained from clinical measurements, with the final goal of associating clinical causes to the three patterns. To our knowledge, we are the first to apply FDT to gait analysis. Chau [21], in a review of analytical techniques for gait data, mentioned that decision trees as a method had not yet been applied to this field. Decision trees can be used to classify pathological conditions, to study the relationship between EMG and kinematics, or to search for patterns/confirm suspect patterns in the data. In this study, FDT was used to link the ankle patterns of toe-walkers to recorded clinical measurements. Unlike feed forward neural networks, rules induced by decision trees create intelligible paths to classification.
The notion of fuzziness introduced by the coding method in this study made it possible to address the problem of inherent variability, inaccuracy and uncertainty in evaluations of muscular strength, muscular spasticity and range of movement. The linguistic terms obtained by fuzzy coding provided rules with intelligible terms that were closer to those used in human reasoning. Fuzziness, then, would appear to be a good way to deal with clinical measurements.

4.2 The accuracy of the method

The classification accuracy (81%) of our method is in the same range as the studies using artificial neural networks in conjunction with clinical biomechanics reported in Schöllhorn's synthesis [22]. In this synthesis, the accuracy of the classifications using gait data with neural networks varied from study to study, but can be estimated at around 80%. In the studies reported by Chau [21], the accuracy of gait parameter prediction using other data types yielded a correlation coefficient that varied between 0.71 and 0.98.
The accuracy of our classification with respect to disease indicates that clinical measurements provide a good explanation for toe-walking in most diseases, but a poor explanation for idiopathic toe-walkers (ITW). The small limitation of dorsiflexion in ITW evoked by Taussig [5] does not seem to be an adequate explanation for toe-walking in these patients. Armand et al. [1] previously reported a strong proportion of ITW who exhibit the same pattern as the present study's group 2, but the rules corresponding to this group are not connected to ITW. In any case, our results leave the causes of toe-walking in ITW unclear.

4.3 Rules interpretation

Among the rules created by FDT (Table 3), rule R1-1, which indicates quadriceps weakness, confirms the causes of toe-walking evoked in the literature [2,23]. Plantarflexion at the ankle (Figure 4c) and absence of knee flexion in stance (Figure 4b) are intentional adaptations designed to create a permanent internal flexor moment at the knee (Figure 4f) and thus compensate for this quadriceps weakness.
Weakness in the tibialis anterior (rule R1-4) hinders the correct pre-positioning of the foot in the swing phase, leading either to a flat-footed contact with the floor or to toe contact alone [2,23]. This is confirmed by excessive plantarflexion during the swing phase (Figure 4c).
The limitation of plantarflexion in the swing phase (Figure 4c), observed for rules R1-2 and R1-3, was evoked by Karol et al. [24] for the case of clubfooted children, though they did suggest that a lack of plantarflexion might be related to weak plantarflexors. Rules 1-2 and rules 1-3 of our study, however, indicate a limitation in the plantarflexion range of motion rather than muscular weakness.

Spasticity in the triceps surae (average for rules R1-5) is a very common cause of toe-walking in cerebral palsy. It is interesting to notice that average spasticity of the triceps surae in conjunction with average spasticity of the quadriceps or low spasticity of the hamstring leads to an ankle pattern like that of our group 1. On the other hand, high spasticity of the triceps surae in conjunction with limited dorsiflexion and quadriceps spasticity (rules R2-1, R2-2) leads to a group 2 ankle pattern. These patterns are similar to Rodda and Graham's jump knee group [25] and to O'Byrne's group 2, which is characterized by a stiff crouch with toe walking [26], with permanent plantarflexion (Figure 5c) and excessive hip and knee flexion (Figure 5a,b). The causes evoked by Rodda and Graham [25] were spasticity of the hamstring and hip flexors, in addition to calf spasticity with co-contraction of the rectus femoris for stiff knee. In our study, all patients classified by these rules presented hamstring spasticity, which did not appear in the rules because it was not a discriminating variable for the classification of patients in group 2. Theses rules could be linked to a fixed contracture of the calf muscles as described by Steinwender et al. [27].

High spasticity in the triceps with a low level of knee extension (Rule R2-3) produces patterns similar to the apparent equinus highlighted by Rodda and Graham [25] with important knee flexion (Figure 5b) and an ankle angle hovering around 0° (Figure 5c). The low level of knee extension measured during the clinical examination could be the result of hamstring contracture.

Hamstring spasticity of the g with a limited range of movement is characterised by rules from group 3 (R3). The amount of gastrocnemius activity at 40% of the gait cycle (Figures 5n,6n) was significant, compared to group 2. The double bump ankle pattern (Figure 6c) associated with this gastrocnemius activity confirms the dynamic calf tightness evoked by Tardieu et al. [28]. The knee flexion at initial contact (Figure 6b) was linked to the high level of hamstring spasticity.

Creating rules to explain three ankle gait patterns in toe-walkers also provides a pedagogic approach permitting a combination of clinical measurements to be linked to one gait pattern. In our opinion, using the same approach backwards—i.e. hypothesizing causes from the gait deviations on gait data charts—would allow a clinician to perform gait interpretation more quickly and more accurately. Because interpreting gait data is one of the most important steps in gait analysis, this step must become more reliable, as Skaggs et al. [7] observed in their study of the variability of gait analysis interpretation and as Simon [29] advised in his article about the limitations and benefits of gait analysis.

5 Conclusion

This study uses FDT to link three major toe-walking patterns to their possible clinical causes, using natural language rules and graphic illustrations. Pattern 1 is essentially characterized by muscular weakness of the tibialis anterior and quadriceps or by an average triceps surae spasticity. Pattern 2 shows high spasticity in the triceps surae associated with a highly limited range of motion at the ankle. Pattern 3 is characterized by an average to high hamstrings spasticity associated with a moderately limited range of motion at the ankle or at the knee. Our set of rules provides a knowledge depository that can be exploited to interpret gait analysis data in toe-walking patients. Querying this knowledge depository could be done manually, but could also be facilitated by a user-friendly computer interface. In any case, improved understanding and interpretation of toe-walking could lead to better therapeutic choices.

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Table 1: Clinical variables with window limits for fuzzy coding**.**

	Clinical variables	Low	Average	High	Units
Range of movement	Hip Flexion	100	120	140	Degree (°)
	Hip Extension	-30	-10	10	Degree (°)
	Knee Flexion	110	130	150	Degree (°)
	Knee Extension	-20	0	20	Degree (°)
	Dorsiflexion	-20	10	40	Degree (°)
	Plantarflexion	0	30	60	Degree (°)
Spasticity	Quadriceps	0	2	4	Ashworth Grade
	Hamstring	0	2	4	Ashworth Grade
	Triceps surae	0	2	4	Ashworth Grade
	Tibias anterior	0	2	4	Ashworth Grade
Manual Muscular Testing	Quadriceps	1	3	5	Grade
	Hamstring	1	3	5	Grade
	Triceps surae	1	3	5	Grade
	Tibias anterior	1	3	5	Grade
	Differencial leg length	0	2	4	cm

Table 2: Results of stratified ten-fold cross validation for each of the Armand toe-walking groups**.**

	General	Group 1	Group 2	Group 3
Accuracy	81%	83%	77%	80%
Sensitivity	65%	60%	67%	67%
Specificity	84%	95%	73%	78%

Table 3: "yes" rules induced from FDT, where n≥3 and the number of conditions ≤ 5.

Rules	p (rule fire strength)	n	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5
R1-1	1.00	22	Low Triceps SPA	Average Quadriceps STR			
R1-2	1.00	3	Low Triceps SPA	High Quadriceps STR	Low Plantarflexion ROM		
R1-3	0.95	8	Low Triceps SPA	Average Plantarflexion			
R1-4	0.97	9	Low Triceps SPA	Average Tibialis Anterior STR			
R1-5	0.77	4	Average Triceps SPA	High Knee Extension ROM	Average Hip Extension ROM	Average Quadriceps SPA	
R2-1	0.77	6	High Triceps SPA	Low Dorsiflexion ROM	Average Quadriceps SPA		
R2-2	1	4	High Triceps SPA	Low Dorsiflexion ROM	High Quadriceps SPA		
R2-3	0.75	5	High Triceps SPA	Average Dorsiflexion	Low Knee Extension ROM	Average Tibialis Anterior STR	Average Plantarflexion
R3-1	0.75	4	Average Hamstring SPA	Average Dorsiflexion	Low Quadriceps SPA	High Hip Extension ROM	
R3-2	1.00	13	Average Hamstring SPA	Average Dorsiflexion	Average Quadriceps SPA	High Hip Extension ROM	High Knee Extension ROM
R3-3	0.81	5	High Hamstring SPA	Average Knee Extension ROM	Average Plantarflexion ROM		
R3-4	0.76	15	High Hamstring SPA	Average Hip Extension ROM	High Dorsiflexion ROM	Average Triceps STR	Average Knee Extension ROM

SPA-Spasticity, ROM-Range of movement, STR-strength;
Rule numbers: R*group-rule;*
n : number of patients used to create a given rule.

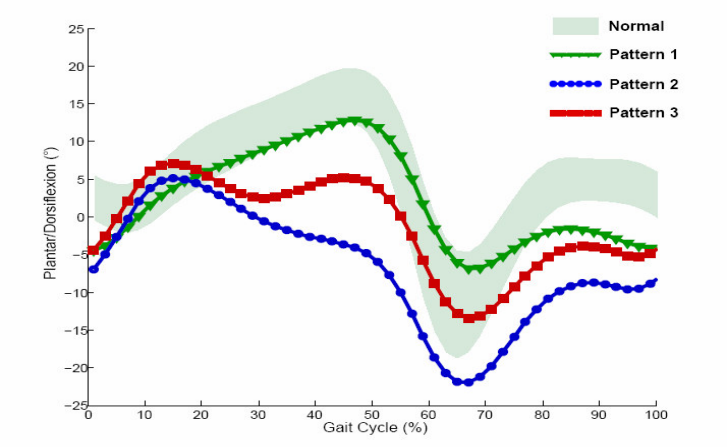

Figure 1: Three kinematic ankle gait patterns, as identified by Armand et al. [1]. The shaded region represents the mean ± one standard deviation based on 20 able-bodied subjects (age: 11.34 ± 3.2 years; height: 1.45 ± 0.27 m; mass: 40.4 ± 5.3 kg).

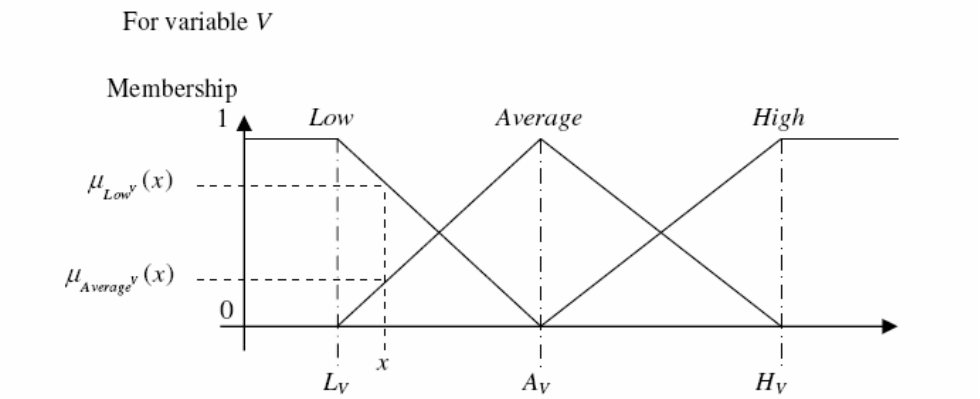

Figure 2: Fuzzy windowing with triangular membership functions used for clinical measurements

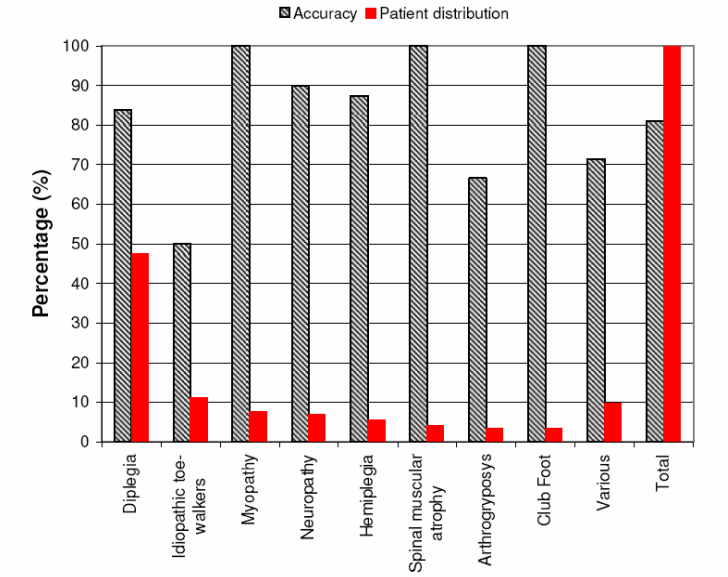

Figure 3: Classification accuracy of the fuzzy decision trees method and patient repartition according to disease.

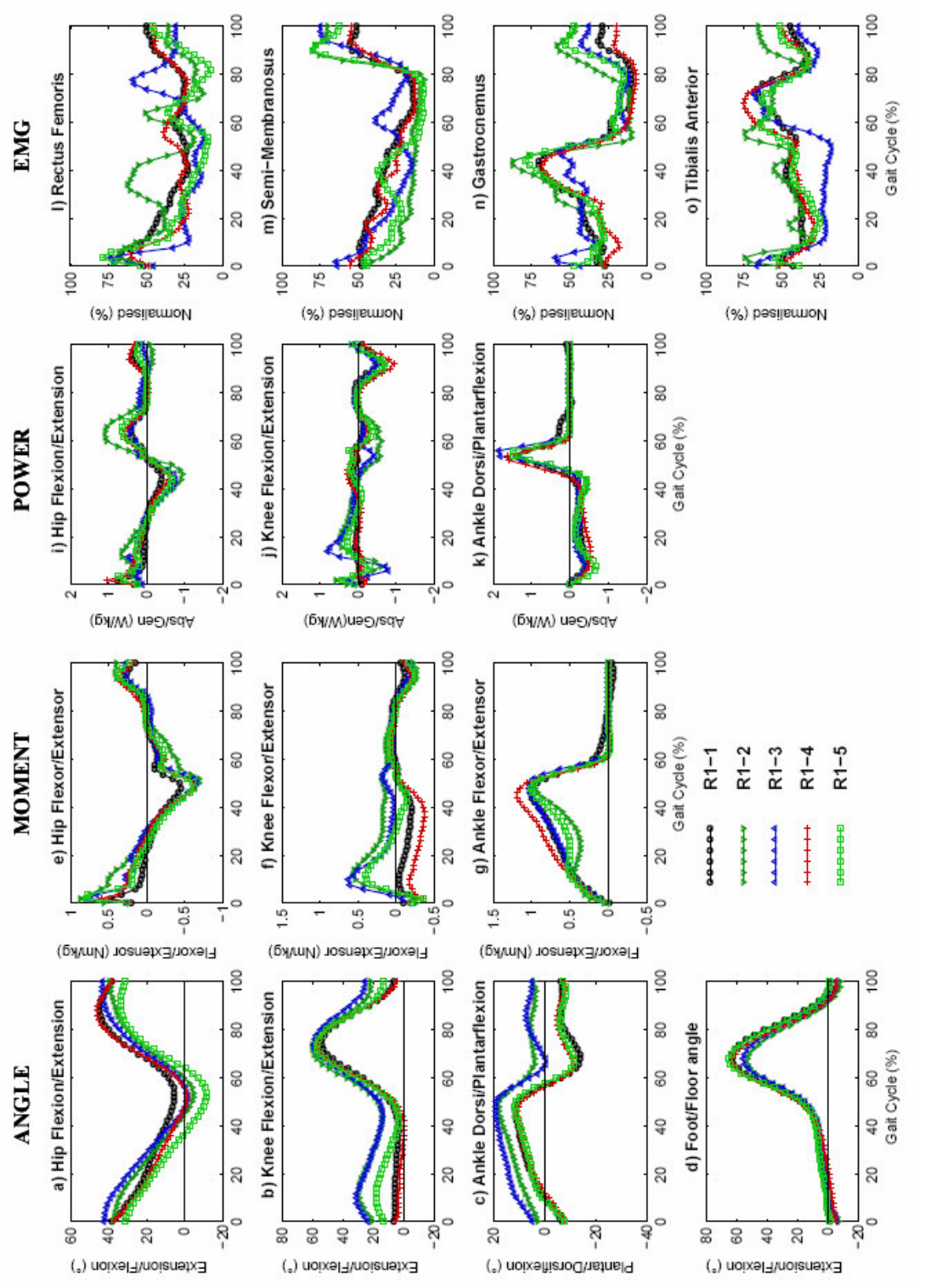

Figure 4: The kinematics (a, b, c, d), internal moments (e, f, g), powers (i, j, k) and EMG (l, m, n, o) of the sagittal plane for the ankle (c, g, k), for the knee (b, f, j) and for the hip (a, e, i) illustrating group 1 rules. For each rule plotted, the average gait waveform is derived from the patients classified with this rule during fuzzy decision tree induction, and weighted according to the patient membership in this rule. All graphs are normalized according to the gait cycle.

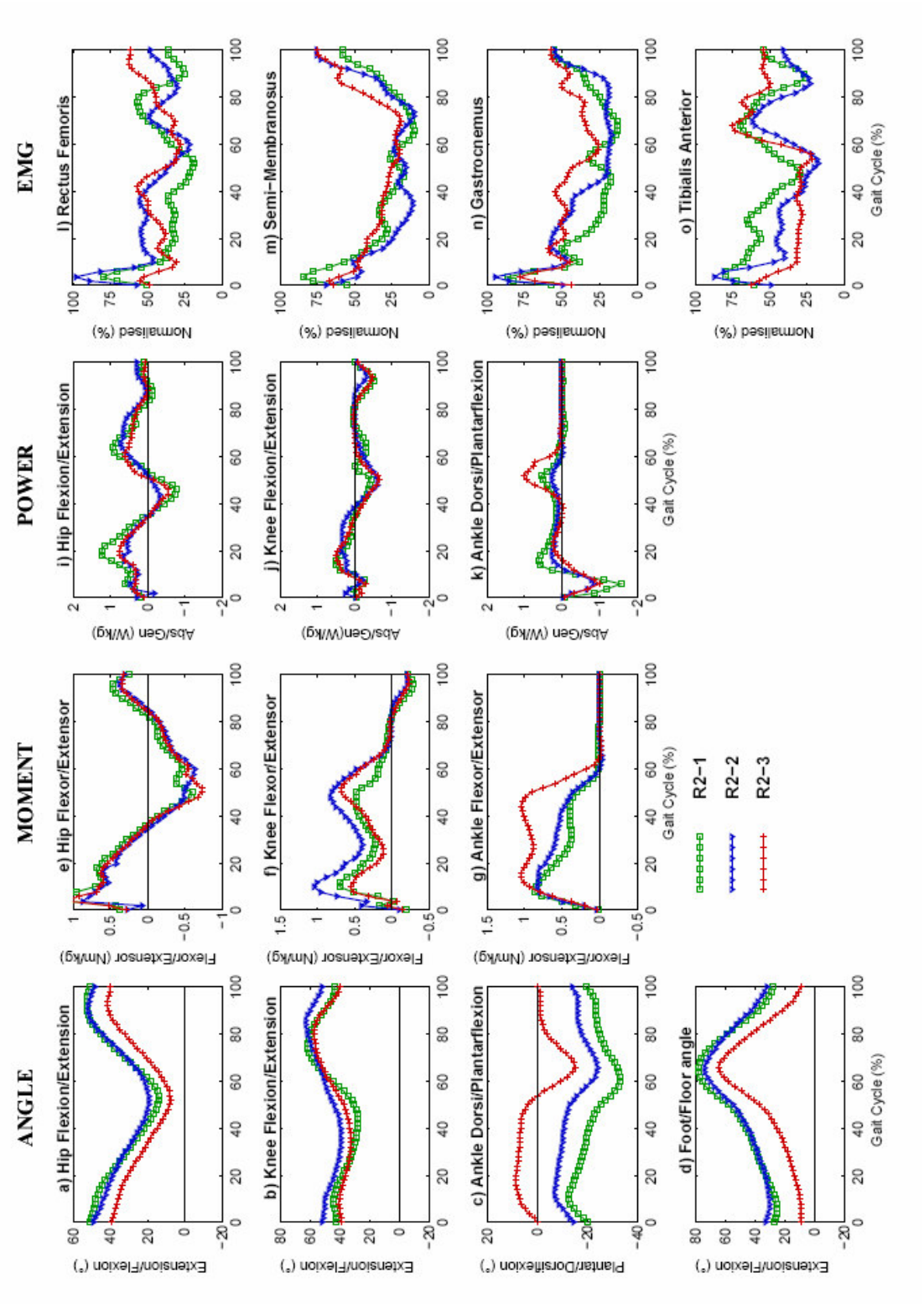

Figure 5: The kinematics (a, b, c, d), internal moments (e, f, g), powers (i, j, k) and EMG (l, m, n, o) of the sagittal plane for the ankle (c, g, k), for the knee (b, f, j) and for the hip (a, e, i) illustrating group 2 rules. For each rule plotted, the average gait waveform is derived from the patients classified with this rule during fuzzy decision tree induction, and weighted according to the patient membership in this rule. All graphs are normalized according to the gait cycle.

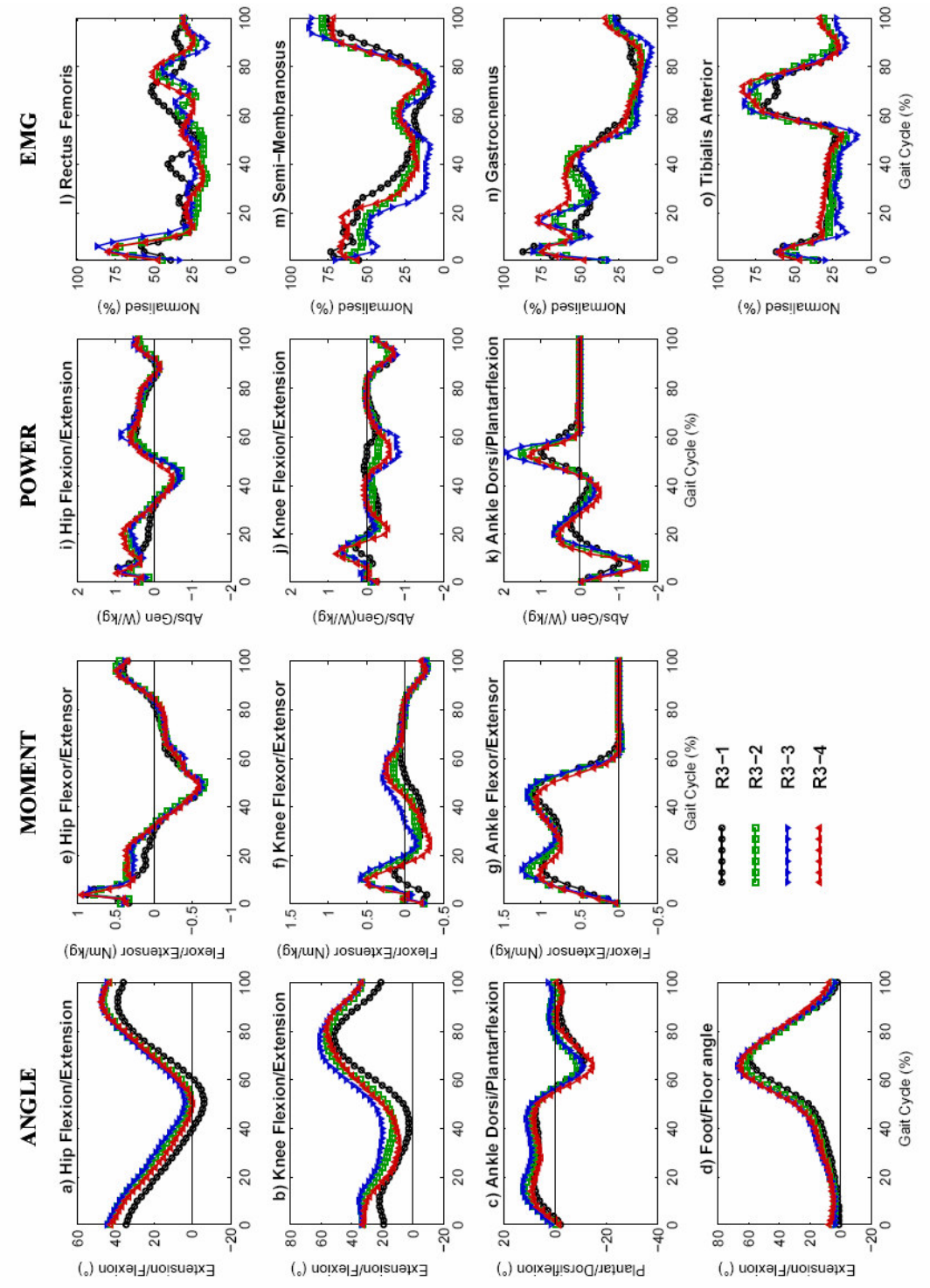

Figure 6: The Kinematics (a, b, c, d), internal moments (e, f, g), powers (i, j, k) and EMG (l, m, n, o) of the sagittal plane for the ankle (c, g, k), for the knee (b, f, j) and for the hip (a, e, i) illustrating group 3 rules. For each rule plotted, the average gait waveform is derived from the patients classified with this rule during fuzzy decision tree induction, and weighted according to the patient membership in this rule. All graphs are normalized according to the gait cycle

Analyse Quantifiée de la Marche : extraction de connaissances à partir de données pour l'aide à l'interprétation clinique de la marche digitigrade

Résumé :

L'Analyse Quantifiée de la Marche (AQM) est un examen permettant d'identifier et de quantifier les défauts de marche d'un patient à partir de données biomécaniques. L'interprétation de cet examen, conduisant à l'explication des défauts de marche, est ardue. Parmi ces défauts, la marche digitigrade est un des plus courants et pour lequel l'identification des causes demeure difficile. Ce travail propose de fournir une aide à l'interprétation des données de l'AQM pour la marche digitigrade.

Afin d'atteindre cet objectif, une méthode d'Extraction de Connaissances à partir de Données (ECD) est utilisée en combinant un apprentissage automatique non-supervisé et supervisé, pour extraire objectivement des connaissances intrinsèques et discriminantes des données de l'AQM. L'apprentissage non-supervisé (c-moyennes floues) a permis d'identifier trois patrons de marche digitigrade à partir de la cinématique de la cheville provenant d'une base de données de plus de 2500 AQM (Institut Saint-Pierre, Palavas, 34). L'apprentissage supervisé est utilisé pour expliquer ces trois patrons de marche par des mesures cliniques sous la forme de règles induites à partir d'arbres de décision flous. Les règles les plus significatives et interprétables (12) sont sélectionnées pour créer une base de connaissances qui est validée au regard de la littérature et des experts. Ces règles peuvent servir d'aide à l'interprétation des données de l'AQM pour la marche digitigrade.

Ce travail ouvre différentes perspectives de recherche allant de la généralisation de la méthode utilisée à la création d'un simulateur de marche pathologique.

Mots Clés : Analyse Quantifiée de la Marche, marche humaine, marche digitigrade, Extraction de Connaissances à partir de Données, apprentissage automatique, aide à l'interprétation, c-moyennes floues, arbres de décision flous, règles floues, explication, classification.

Clinical Gait Analysis: using knowledge discovery in databases to aid in the clinical interpretation of toe-walking

Abstract:

Clinical Gait Analysis (CGA) is used to identify and quantify gait deviations from biomechanical data. Interpreting CGA, which provides the explanations for the identified gait deviations, is a complex task. Toe-walking is one of the most common gait deviations, and identifying its causes is difficult. This research had for objective to provide a support tool for interpreting toe-walker CGAs.

To reach this objective, a Knowledge Discovery in Databases (KDD) method combining unsupervised and supervised machine learning is used to extract objectively intrinsic and discriminant knowledge from CGA data. The unsupervised learning (fuzzy c-means) allowed three toe-walking patterns to be identified from ankle kinematics extracted from a database of more than 2500 CGA (Institut Saint-Pierre, Palavas, 34). The supervised learning was employed to explain these three gait patterns through clinical measurement using induced rules from fuzzy decision trees. The most significant and interpretable rules (12) were selected to create a knowledge base that has been validated in terms of the literature and experts. These rules can be used to facilitate the interpretation of toe-walker CGA data.

This research opens several prospective paths of investigation, ranging from the development of a generic method based on the proposed method for studying movement to the creation of a pathologic gait simulator.

Keywords: Clinical Gait Analysis, human gait, toe-walking, Knowledge Discovery in Database, machine learning, interpretation support, fuzzy c-means, fuzzy decision trees, fuzzy rules, explanation, classification.