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IDENTIFICATION OF TIME-VARYING ANKLE STIFFNESS

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Abstract

The joint stiffness plays a significant role during movement; however its function is not fully understood, particularly in terms of reflex contributions. Studies examining the mechanical consequences of reflex activity during movement are few. The long term objective of this thesis was to develop and validate a method for identifying joint mechanics during movement.

Previously developed ensemble, time-varying algorithms were used to extend the parallel-cascade model to non-stationary conditions. This algorithm was tested using simulated data. We obtained parameter estimates of ankle stiffness from experiments under stationary conditions and used them to create a simulated system undergoing a ramp displacement. Data was acquired from three subjects as an electro-hydraulic actuator imposed a ramp displacement with superimposed perturbations to the ankle. The algorithm performed well with simulated data. Experimental system estimates were good at certain times and not at others, because the ensemble input was not rich enough to permit a good identification.

Résumé

La raideur d'un joint joue un rôle significatif pendant le mouvement; mais sa fonction n'est pas entièrement comprise, particulièrement en ce qui concerne les contributions du réflexe. Il existe peu d'études examinant les conséquences mécaniques du réflexe pendant divers mouvements. L'objectif à long terme de cette thèse était de développer et de valider une méthode pour identifier la raideur articulaire pendant divers mouvements.

Des techniques, précédemment développées pour l'identification de systèmes nonstationnaires, ont été utilisées afin d'appliquer le modèle « cascade-parallèle » aux conditions non-stationnaires. Cet algorithme a été évalué en utilisant des données simulées. Nous avons estimé des paramètres de raideur de la cheville à partir d'expériences en régime stationnaire et les avons ensuite utilisés pour créer un système simulé subissant un déplacement en rampe. Des données ont été acquises de trois sujets pendant qu'un actionneur électro-hydraulique imposait à leur cheville un déplacement en rampe avec des perturbations superposées. L'algorithme a bien exécuté avec les données simulées. Les estimations des données expérimentales était bonnes à certains instants et peu faibles à d'autres, parce que les données de l'ensemble n'avaient pas assez d'information pour permettre une bonne identification.

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1. Introduction

The neuromuscular control system is characterized by complex interactions between the nervous system and the musculoskeletal system. In order for you to sit, stand or walk as you read this thesis, your neuromuscular control system must maintain your balance and perform movements of variable speed and variable precision. It processes a variety of information, from sensory feedback coming from peripheral receptors (i.e. muscle spindles) to central commands coming from the brain. The study of joint mechanics and the neuromuscular control system allows us to better understand the control of movement, posture, and its disorders.

1.1 Joint Dynamics and the Stretch Reflex

Dynamic joint stiffness can be used to describe the mechanical behaviour of a joint and is defined as the relationship between the position of the joint and the torque acting about it [1]. Joint stiffness can be separated into two components: (1) an intrinsic stiffness component, due to the mechanical properties of the joint, passive tissue and active muscle fibres, and (2) a reflex stiffness component, due to muscle activity in response to the activation of stretch receptors, called muscle spindles, within the muscle.

Much has been discovered physiologically about the stretch reflex, but its functional significance only becomes apparent when investigating joint dynamics. The two components of dynamic joint stiffness are challenging to quantify, but provide great insight into the neuromuscular control system when performing studies on posture and movement.

In our laboratory, we are capable of measuring the angular position of a subject's ankle and the torque generated at the ankle. The subject lays supine with their ankle attached to an electrohydraulic actuator via a custom-fit, fibreglass boot. A proportional, position-control servo applies perturbations to the ankle. Novel system identification tools have been developed to fully characterize the two stiffness pathways during stationary, or postural, experimental conditions. To study non-stationary behaviour, such as voluntary movement, time-varying identification techniques must be used. In this thesis, we developed novel time-varying identification tools and used them to study a simple time-varying behaviour.

1.2 Identification of Time-Varying Joint Dynamics

System identification allows the creation of a mathematical model of a system (i.e. joint stiffness) based on measured inputs and outputs [2]. Previous work in our laboratory led to the development of a parallel-cascade model that represents the intrinsic and reflex pathways of stiffness [3]. Its elements can be reliably identified from position input and torque output records acquired under stationary conditions. Recently two time-varying identification techniques, one for linear intrinsic stiffness and the other for nonlinear reflex stiffness, were developed for use with ensemble data acquired under non-stationary conditions [4]. Separate simulations tested each technique and demonstrated their ability to identify rapidly time-varying dynamics of the ankle joint [4].

The overall goal of this thesis was to develop and validate a method for identifying joint mechanics during movement. This involved integrating the previous time-varying techniques into the parallel-cascade model. The first objective was to evaluate the quality of the time-varying, parallel-cascade identification algorithm using simulated data. We obtained parameter estimates of ankle stiffness from experiments under stationary conditions and then used them to create a simulated system undergoing a ramp change of position. Position input and resulting torque output records were obtained over multiple realizations. The time-varying, parallel-cascade identification algorithm was applied to the simulated input-output ensemble data. The true and identified systems were compared and found to be similar, for both stiffness pathways.

The second objective was to test the identification algorithm with experimental data obtained during time-varying conditions. A simple, imposed-ramp paradigm was investigated for three subjects. The results showed an increase in intrinsic stiffness and reflex stiffness during the ramp. However, using this particular input perturbation the system estimates did not describe the data well at certain times.

1.3 Thesis Outline

The thesis is divided into six chapters including this introduction. Chapter Two covers the physiology background of the stretch reflex, and describes joint dynamic stiffness and its role during voluntary movement. System identification is introduced along with techniques developed in our laboratory. The chapter concludes with the aims and motivation of this thesis. The experimental setup is presented in Chapter Three, and gives details on the sensors, experimental control, and data acquisition. Chapter Four provides details on the time-varying, parallel-cascade identification algorithm. The simulation study is presented, along with the results and discussion. The fifth chapter explains the experimental protocol and data analysis used to study the time-varying behaviour. The experimental results are presented and discussed. The final chapter summarizes the results, provides a general discussion, and suggests directions for future work.

2. Background

This chapter introduces the physiology of the ankle joint and the peripheral neuromuscular system. Skeletal muscle structure and the events leading to and during muscular contraction are presented. Sensory stretch receptors and peripheral reflexes are described followed by an introduction to joint dynamic stiffness. A brief review of the literature on joint dynamic stiffness during voluntary movement is presented. System identification is introduced and specifically time-varying techniques are discussed. The time-varying, ensemble-based methods developed in our laboratory are presented. To conclude, the objectives and motivation of this thesis are discussed.

2.1 Ankle Joint

A joint is composed of the associated bones, musculature and passive tissues (i.e. tendons, ligaments), which contribute to its overall mechanical behaviour. The **ankle joint**, or **talocrural joint**, is made up of four major bones: the tibia and fibula of the lower leg which articulate with the talus and calcaneus bones of the foot [5]. This synovial, hinge joint allows movement in two planes: sagittal and frontal. The sagittal movements are termed **dorsiflexion**, pulling the toes towards the leg (anterior side), and **plantarflexion**, pointing the toes away from the leg. The frontal movements of adduction and abduction were not studied in this thesis. The main bones and muscles at the ankle joint are shown in Fig. 2.1.

Dorsiflexion results primarily from the contraction of the muscle **tibialis anterior (TA)** which originates at the tibia and inserts at the base of the first metatarsal bone via the tibialis anterior tendon [6]. The muscles primarily responsible for plantarflexion are the **gastrocnemius** and **soleus (GS)**, grouped as the **triceps surae**. The gastrocnemius is attached to the femur and via the calcaneal (Achilles) tendon to the calcaneus, thus spanning the knee and ankle joints. Underlying the gastrocnemius is the soleus, which is attached to the head of the fibula and a portion of the medial tibia, and shares the Achilles tendon attachment with the gastrocnemius [6].



Figure 2.1: Posterior view (left) and medial view (right) of ankle joint bones, tendons and muscles [adapted from 6]

2.2 Peripheral Neuromuscular System

The nervous system can be divided into two major anatomical subdivisions: (1) the **central nervous system (CNS)**, which consists of the brain and spinal cord, and (2) the **peripheral nervous system (PNS)**, which includes all sensory or neural tissue outside of the CNS. Specific motor control elements in the brain have been identified in the brainstem, cerebellum, basal ganglia, and cortical areas [7].

The role of the PNS is to deliver sensory and motor information via bundles of nerve fibres, called peripheral nerves. A further division of the PNS is made to differentiate between sensory information being brought to the CNS (afferent division) from receptors in peripheral tissues and organs, and motor commands being carried **from the CNS (efferent division)** to peripheral tissues (i.e. muscles).

2.2.1 Skeletal Muscle Structure

To comprehend the physiological mechanisms of muscle, the structure of skeletal muscle must be understood. Skeletal muscle consists of many cylindrical **muscle fibres**, each composed of one elongated cell with multiple nuclei. Muscle fibres in adults may be up to 20 cm in length and have diameters between 10 and 100 μ m [7]. Muscle fibres are composed of **myofibrils** lying parallel to one another that are striped in appearance due to the arrangement of their thick and thin protein filaments, as illustrated in Fig. 2.2.

The repeating unit in the myofibril is called the **sarcomere**, the basic functional unit of a muscle. A sarcomere consists of thin **actin** and thick **myosin** filaments lying in parallel and has a resting length between 1.6 and 2.6 μ m [6]. Thick and thin filaments are typically 10-12 nm and 5-6 nm in diameter, and 1.6 μ m and 1 μ m in length, respectively [6].

The thick filaments consist primarily of myosin molecules. Myosin molecules have a long tail portion from which extents a globular head containing a binding site for actin [5]. Two intertwined helical chains of actin molecules form the backbone of the thin filaments. Secondary components in thin filaments include **troponin** and **tropomyosin**. Tropomyosin molecules block the myosin-binding site on each actin molecule and are held in place by troponin. As depicted in Fig. 2.2, the actin filaments are anchored to a structure of interconnecting proteins known as the Z line [7].



Figure 2.2: Skeletal Muscle Structure [7]

Muscle contraction is initiated when a skeletal muscle has been excited (described in Section 2.2.3) and briefly occurs as follows [7]:

- Calcium binds to specific binding sites on troponin causing a change in its shape. The modified troponin drags away the tropomyosin to expose the myosin-binding site on each actin molecule.
- 2) The myosin globular heads bind to the actin forming cross-bridges.
- 3) The myosin head generates the power stroke to slide the actin filament past itself resulting in the overall shortening of the sarcomeres. The energy required for the cross-bridge movement comes from the hydrolysis of a high energy molecule called adensosine triphosphate (ATP).
- 4) To repeat the cross-bridge cycle, ATP binding to myosin breaks the link between actin and myosin.
- 5) When calcium is removed from troponin, the myosin-binding sites on actin are no longer exposed, which stops the contractile activity.

2.2.2 Motor Units

The excitation required for muscle contraction originates in nerve cells, called **alpha** (α) motor neurons. The cell bodies of motor neurons originate in the anterior horn of the spinal cord and their axons travel down peripheral nerves to the muscles [7]. A muscle fibre is innervated by the axon of only one motor neuron, yet a motor neuron innervates many fibres as its axon divides into branches.

A **motor unit** consists of the motor neuron, its axon and all the muscle fibres it innervates. All fibres in a motor unit contract each time the motor neuron fires, thus making the motor unit the smallest functional element of the motor system. Depending on the muscle function, the number of fibres in a motor unit varies. For example, in an eye muscle which generates fine movements, there are only about 13 fibres per axon [7]. In contrast, leg muscles required for large, coarse movements contain hundreds of fibres per axon.

2.2.3 Action Potentials and the Neuromuscular Junction

To understand how the cross-bridge cycle is initiated, the process called **excitation-contraction coupling** must be presented. In general, this process can be described as the transmission of electric signals along nerve fibres, across the neuromuscular junction and along muscle fibres, which leads to cross-bridge formation [5]. In this section, the events of the excitation-contraction coupling process are described in more detail.

An **action potential (AP)** is a sudden change in the membrane potential of a nerve cell that propagates along the length of the axon. Referring to Fig. 2.3, the steps involved in action potential generation in a motor neuron will be briefly described [6]:

- The cell membrane has a resting membrane potential of -70 mV. If an area of excitable membrane is depolarized by local currents above a threshold of -60 mV, an AP will be generated.
- 2) When the membrane potential reaches threshold, voltage-regulated sodium channels, which are closed in the resting state, are opened. The resulting inrush of sodium ions into the cytoplasm causes a rapid depolarization of the membrane.

- When the membrane potential approaches +30 mV, sodium channels begin to close and voltage-regulated potassium channels begin to open. Thus a repolarization of the membrane occurs.
- 4) As the potential returns to its resting state, the potassium channels close.



Figure 2.3: Changes in membrane potential during action potential (AP) generation [6]

Action potentials propagate along an axon because adjacent sections of the membrane are subjected to local currents generated from the AP. These currents depolarize the membrane and the sequence of events described above is repeated along the axon. Skeletal muscle fibres have excitable plasma membranes and thus are capable of generating and propagating APs by mechanisms similar to those described for motor neurons. The resting potential of a muscle fibre, due to sodium and potassium ion concentrations, is approximately -90 mV. With sufficient stimulation, the muscle fibre potential may increase up to 30-40 mV [6].

The transformation from AP propagation in motor neurons to AP propagation in muscle fibres occurs at the neuromuscular junction. The **neuromuscular junction (NMJ)** is the connection between the end of a motor neuron axon's branch, or **synaptic**

terminal, and the muscle fibre it innervates. The synaptic terminal contains vesicles filled with a neurotransmitter called acetylcholine (ACh). Along the sarcolemmal surface of the muscle fibre there are membrane receptors that bind ACh and this surface is known as the **motor end plate**. The **synaptic cleft** is the narrow space between the synaptic terminal and the motor end plate [7].

The events that occur at the NMJ are depicted in Fig. 2.4. The arrival of an action potential at the synaptic terminal causes ACh to be released into the synaptic cleft. As the ACh molecules bind to the motor end plate receptors, the permeability of the sarcolemmal to sodium ions increases. Therefore sodium ions move rapidly through the sarcolemmal and produce local currents. These currents lead to an action potential being generated in the muscle fibre. Cross-bridge formation is then initiated.



Figure 2.4: Events occurring at the neuromuscular junction (NMJ) for action potential (AP) generation in muscle fibres [7]

2.2.4 Control of Muscle Force

Two main factors control the tension produced by an entire skeletal muscle: the frequency of **motor unit action potential (MUAP)** firing and the number of motor units stimulated. As the MUAP firing rate increases, the tensions produced by the individual action potentials summate to create an overall increase in muscle tension. This effect is clearly illustrated in Fig. 2.5, where the tension produced from a single twitch is compared with the tension produced from multiple stimuli at different frequencies.

Unfused tetanus, shown in the middle of Fig. 2.5, occurs at low stimulation frequencies, where the muscle enters the relaxation phase and produces an oscillating tension [7]. When the MUAP firing rate is increased such that the muscle never enters the relaxation phase, the muscle is said to be in **fused tetanus**, illustrated on the right of Fig. 2.5. Most normal activities involve fused tetanus of the activated muscles [6].



Figure 2.5: Relative muscle tension produced from a single twitch (left), from multiple stimuli (represented by 'S') applied at 10 stimuli per second (middle), and from multiple stimuli applied at 100 stimuli per second (right) [7]

Recruitment, or multiple motor unit summation, is the smooth, steady increase in muscle tension resulting from an increase in the number of active motor units [6]. It occurs based on the **size principle**: the smallest motor units that contract slowly but fatigue slowly are stimulated first, followed by larger motor units that contract rapidly but fatigue rapidly [7]. Factors affecting recruitment are the axon diameter, axon conduction velocity, and motor neuron cell body size.

2.2.5 Peripheral Sensory Receptors

Sensory receptors are stimulated by physical or chemical changes in the body or by changes in the external environment. **Proprioceptors** are sensory receptors that perceive the position of the body in space by detecting position and force information. Two types of proprioceptors thought to be primarily responsible for muscle regulation are: muscle spindles and Golgi tendon organs (GTO).

2.2.5.1 Muscle Spindles

Sensory stretch receptors are endings of afferent fibres that are wrapped around modified muscle fibres called **intrafusal fibres**. Several of these intrafusal fibres are enclosed in a connective-tissue capsule, as illustrated in Fig. 2.6, and the entire structure is called a **muscle spindle** [7]. Muscle spindles sense changes in muscle length and velocity. Intrafusal fibres lie in parallel with the muscle, thus changes in muscle length are reflected in the intrafusal fibres.

Sensory information from the muscle spindles is carried via afferent fibres to the spinal cord. There are two types of sensory nerves: **primary (Group Ia)** and **secondary (Group II)** fibres. Group Ia fibres are myelinated nerves of large diameter (12-20 μ m) and terminate as coiled unmyelinated endings that wrap around the non-contractile central portions of the intrafusal fibres. Group II fibres are unmyelinated nerves of small diameter (4-12 μ m), whose endings terminate on the peripheral contractile end of the intrafusal fibres. Group II fibres only make synapses via interneurons, whereas Group Ia fibres also synapse directly with the motor neurons. There is only one primary ending for each spindle, but multiple secondary endings in each spindle.

Studies using sinusoidal stretch inputs have refuted claims that secondary endings are insensitive to dynamic components of stretch. The frequency responses of both Ia and II afferents are both high pass dynamics, with a break-point at approximately 1 Hz [8]. However, the conduction of information in Group Ia afferents is faster (70-120 m/s compared to 20-70 m/s) than in Group II afferents. Primary afferents are more sensitive to smaller amplitude stimuli as compared with secondary afferents. Furthermore, Ia afferents are sensitive to acceleration at high frequencies and have a smaller linear range [8].

Efferent fibres called **fusimotor** (γ) motor neurons carry information from the spinal cord to the spindle intrafusal fibres. Fusimotor innervation controls the spindle sensitivity during muscle contraction. The polar ends of the intrafusal fibres contract in response to fusimotor neuron activation. This stretches the central non-contractile portion of the spindle, making it more sensitive to stretch [7]. There are two types of fusimotor neurons that alter the responsiveness of spindles. **Dynamic** γ activity tunes the Ia afferents to the dynamic phase of stretch (i.e. velocity), and **static** γ activity increases the sensitivity of both Ia and II afferents to the static phase of stretch (i.e. muscle length) [8].



Figure 2.6: Muscle Spindle and Golgi tendon organ [7]

2.2.5.2 Golgi Tendon Organs (GTO)

Sensory receptors called the **Golgi tendon organs (GTO)** monitor the tension produced in the tendon from muscle contraction. The GTOs are afferent nerve endings wrapped around collagen bundles in the tendon, as shown in Fig. 2.6. Contrary to muscle spindles, GTOs are assembled in series with some muscle fibers and in parallel with others. This leads to increased sensitivity of the receptors to active muscle tension, but less sensitivity to passive muscle tension.

When the extrafusal muscle fibres contract, they pull on the tendon, which stretches the collagen bundles and distorts the receptor endings. The GTOs are activated by this distortion and thus fire in response to the tension generated by the contracting muscle [7]. The receptors are innervated by a single Group Ib afferent axon.

2.2.6 Peripheral Reflexes

Many types of reflexes involve a muscular response; however we are primarily interested in single limb reflexes during active muscle contraction. The **stretch reflex** is investigated in our laboratory, but first, to continue from the previous section, we will describe the reflex resulting from the activation of the GTOs.

When the collagen fibres are stretched, the Group Ib afferents from the GTOs stimulate inhibitory interneurons that in turn inhibit the motor neurons controlling the muscle that is producing the stretch [6]. These interneurons also stimulate the motor neurons of the antagonistic muscles. Thus this **tendon reflex**, or the **inverse stretch reflex**, is the body's mechanism to prevent the tendon from tearing or breaking.

2.2.6.1 The Stretch Reflex

When a skeletal muscle is stretched, the change in muscle length is sensed by the muscle spindles. Group Ia afferent fibres from the spindles transmit a signal into the spinal cord where they synapse directly with the motor neurons controlling the muscle that was just stretched. This monosynaptic pathway is known as the **stretch reflex arc**, and is illustrated by path A in Fig. 2.7. Muscle contraction occurs approximately 20-50 ms after the stretch was initiated [6]. This resistance to elongation occurs in basically every extensor or flexor skeletal muscle in the body and is called the **stretch reflex**.

Group Ia afferent fibres also innervate motor neurons of agonistic muscles (path C in Fig. 2.7), whose contraction would assist in the intended motion of the stretched muscle. Conversely these afferent fibres synapse with interneurons (path B in Fig. 2.7) that in turn inhibit motor neurons of antagonistic muscles, whose contraction would oppose the intended motion of the stretched muscle. The activation of agonist muscles and simultaneous inhibition of antagonistic muscles is called **reciprocal innervation** and is present in many reflexes (e.g. the reciprocal innervation of the spindle afferents is the opposite of that produced by the GTOs). The muscle length and velocity information is conveyed to higher centres of motor control in the brain via a final afferent pathway involving interneurons, as shown by path D in Fig. 2.7 [7].



Figure 2.7: Pathways involved in the stretch reflex, specifically for the knee jerk reflex. The patellar tendon is tapped which stretches the extensor muscle, causing contraction of the stretched muscle and agonist muscles (paths A and C), relaxation of antagonistic muscles (path B), and muscle length information sent to the brain (path D) [7].

Factors that affect the stretch reflex include the level of fusimotor activity and the mechanical properties of the muscle. The sensitivity of the spindle afferents to stretch depends on the level of fusimotor activity. Muscle mechanics determine the force produced in reaction to a neural command. The reflex is elicited by a rapid muscle stretch, as shown in the knee jerk reflex in Fig. 2.7, and can be quantitatively described by measuring position and torque, as presented in Sections 2.3 and 2.4, or by recording electromyographic (EMG) signals, described next [9].

2.2.7 Electromyography (EMG)

Electromyography (EMG) is the measurement of the electrical activity of a muscle. If a rapid stretch is applied to the ankle in dorsiflexion, the EMG response of the gastrocnemius-soleus clearly depicts a large burst of activity at a latency equal to the reflex delay. Thus EMG can be used to quantitatively evaluate the stretch reflex.

An EMG signal records the spatial-temporal summation of **motor unit action potentials (MUAPs)**. EMG signals can be recorded from the surface of actively contracting muscle and represent the combination of multiple motor units firing at different mean rates [5].

EMG signals may be analyzed in the time or frequency domain. One important parameter to describe the power spectrum (frequency domain) is the bandwidth. EMG signals contain usable energy in the range of 0-500 Hz, with a bandwidth of approximately 50-150 Hz. The amplitude of the signal can range from approximately 0-10 mV (peak-to-peak).

Indwelling electrodes are those used directly within the muscle, whereas surface electrodes are placed on the skin overlying the muscle. Surface EMG is used in our laboratory since we are interested in a general picture of the electrical activity from relatively large muscles.

2.3 Joint Dynamic Stiffness

Studying the dynamics of joints enables us to understand more about the neuromuscular control system, as they represent crucial properties of the motor system. Joint dynamics determine the displacements that occur from perturbation forces or the forces that must be generated to execute a voluntary movement [1].

The mechanical behaviour of a joint may be described by its dynamic stiffness. **Dynamic joint stiffness** is defined as the relation between the position of the joint and the torque acting about it [1]. Stiffness can be separated into two components, as depicted in Fig. 2.8:

1) An **intrinsic** component due to the passive visco-elastic and inertial properties of the limb, joint and connective tissues, together with the active muscle mechanical properties, and;

 A reflex component due to muscle activity in response to the activation of stretch receptors in the muscle.



Figure 2.8: Intrinsic and reflex components of dynamic joint stiffness

2.3.1 Views on Stiffness Function

The stiffness of a joint enables the body to maintain and adjust certain postures and plays a significant role during movement; however neither role is fully understood as yet, particularly in terms of the reflex contributions. Joint stiffness can be modulated and evidence points to various methods of modulation via the nervous system. It has been suggested that the nervous system modifies muscle [10, 11], joint [12, 13] or endpoint [14] stiffness to initiate voluntary movement and/or respond to external perturbations.

Mechanically, reflex stiffness is challenging to understand, since there are complex, nonlinear interactions occurring between the two stiffness components. Furthermore reflex stiffness has been found to vary with the operating point, task, time, and context [15]. The mechanical results of the stretch reflex have only been measured for a limited number of tasks and behaviours. More studies on a variety of tasks and behaviours may provide evidence to support the theory that the central nervous system (CNS) modifies the stretch reflex function depending on the task, phase and intensity during a particular behaviour [9]. Moreover, the role of joint stiffness during movement must be thoroughly investigated.

2.3.2 Stiffness Modulation during Voluntary Movement

The role of the stretch reflex in initiating and controlling voluntary movements is not clearly understood. However there are two main views: one central and one peripheral. The first view maintains that a central pattern generator (CPG) controls the timing and course of muscle activation for movement [16, 17]. The second view suggests that reflex parameters are modified via descending pathways to perform active movements [18-20]. It is likely that both theories occur, but for different types of movements.

Many studies have measured changes in the stretch reflex from H-reflex or EMG responses during movement [21, 22]. Similarly, during particular tasks such as walking [23], running [24], beam balancing [25], pedaling [26, 27], and cyclic tracking tasks [28] it has been shown that spinal EMG reflex responses vary throughout the movements. Work in our laboratory has supported the view of peripheral involvement in producing the modulation of reflex stiffness during movement [29]. In this study, pre-recorded walking movements were imposed at the ankle via a hydraulic actuator while the subjects lay supine. Pulse perturbations were superimposed throughout the walking cycle to evoke the stretch reflex. Reflex EMG modulation and magnitude reduction occurred throughout the step cycle and since central commands were kept constant during the experiment, these changes were attributed to peripheral mechanisms.

Because movement studies are generally more challenging to perform than postural studies, it was natural to propose that the results obtained in postural conditions could be used to infer behaviour during voluntary movement at corresponding operating points. However findings about the stretch reflex during postural conditions are generally not applicable to movement [29]. For example, the reflex gain has been found to be larger in postural conditions than during movement at similar operating points and is modulated during cyclic activities [19].

Although a variety of studies have examined the stretch reflex during movement, there remains a void in terms of the mechanical consequences of reflex activity during movement. A recent contribution was made by Bennett et al who used frequency domain analysis to track intrinsic and reflex stiffness throughout rapid elbow movements with superimposed sinusoidal position perturbations [30] and pseudo-random binary sequence (PRBS) force inputs [31]. During the voluntary movement studied with imposed PRBS perturbations, the overall stiffness of the elbow decreased. The overall stiffness values during the movement were found to be significantly smaller than those recorded in postural conditions at corresponding positions [31]. In another study by Bennett, imposed step perturbations were applied to the elbow during voluntary flexion movements of variable speeds and the mechanical properties of the elbow were found to be 'tuned' according to the speed of the movement [32]. Bennett examined the stretch reflex response during a voluntary movement with imposed sinusoidal position perturbations. He found that the mechanical contribution of the stretch reflex increased near the end of the movement (as the target was approached), to a maximum level that accounted for a significant portion of the overall stiffness when using low frequency perturbations [30].

The long term goal for this thesis is to contribute to this void in movement studies by measuring the mechanics of the stretch reflex during movement. The next section describes how we will develop the tools which allow tracking of rapidly time-varying systems, such as those encountered during voluntary movement.

2.4 System Identification

A **system** can be described as the process(es) or physical component(s) that produce an output signal(s) [2]. External signals imposed on the system to produce measurable outputs are called inputs. The term **system identification** involves creating a mathematical model of a system based on measured inputs and outputs [2].

A system is **linear** if it obeys the law of superposition, which means that if a system is presented with a sum of inputs, then the system response will be a sum of the individual responses to the respective signals. Systems that are not found to be linear are called **nonlinear**. **Time-invariant** systems have properties that do not change with time. Conversely, a system whose properties change with time is said to be **time-varying**.

Models of a system can be classified as either **nonparametric** or **parametric** (analytical). Nonparametric identification techniques do not assume a model structure and solve for a numeric representation of the system. Parametric models describe the system by a mathematical or analytic expression [1]. These models are often easier to interpret and require fewer parameters for the model description, compared with nonparametric

techniques. However the catch is that the system will only be properly characterized if the chosen form of the expression is correct.

2.4.1 Impulse Response Function (IRF)

A system's **impulse response function (IRF)** is the response to a unit impulse, which completely characterizes the dynamics of the system [2]. Impulse response functions are formulated in the time domain and have represented linear, nonparametric models for joint dynamics well [1]. Given a linear, time-invariant system's two-sided IRF, the output y(t) to any given input u(t) can be determined using the convolution integral [2]:

$$y(t) = \int_{-\infty}^{\infty} h(\tau)u(t-\tau)d\tau$$
(2.1)

where $h(\tau)$ is the system's IRF or weighting function and τ is the IRF time, or lag, where positive values represent system memory and negative values represent system anticipation.

Similarly for linear, time-varying systems, the dynamics can be described by a **time-dependent weighting function** $h(t,\tau)$. There are various formulations of the time-varying convolution integral, and one possible expression is [33]:

$$y(t) = \int_{-\infty}^{\infty} h(t,\tau) u(t-\tau) d\tau$$
(2.2)

Thus $h(t,\tau)$ corresponds to the response y(t) to a unit impulse applied at time $t-\tau$.

More complex approaches must be used for nonlinear systems and these include the following nonparametric methods: quasi-linear methods, functional expansions and cascade methods [1]. **Quasi-linear** models allow the system to be described at particular operating points, where the system behaves linearly to inputs of small deviations about the operating point. These models hold for stationary (time-invariant) conditions, but may not necessarily be valid in cases where the operating point changes in time. **Functional expansions** involve series expansions such as Volterra or Wiener, whose kernels will characterize the nonlinear system [34]. Many kernels parameters must be estimated which increases the computational time significantly. Also kernels of higher orders are challenging to interpret.

Cascade or **block-structured** models are descriptions that combine static nonlinear and dynamic linear subsystems [34]. A **static** system is one whose output at time t depends solely on the value of the input at time t. Block-structured models can be easily adapted to the time-varying case, by having each subsystem's model vary with time. A parallel-cascade model has been used extensively in our laboratory to identify ankle joint stiffness and is presented next.

2.4.2 Parallel-Cascade Model of Joint Mechanics

The parallel-cascade model of joint mechanics developed in our laboratory is illustrated in Fig. 2.9 [3]. The upper linear pathway represents intrinsic stiffness by a dynamic linear system. The lower nonlinear pathway represents reflex stiffness by a differentiator in series with a Hammerstein system. A **Hammerstein system** is itself a cascade system with a static nonlinearity in series with a dynamic linear subsystem. During postural conditions, this model represents ankle joint mechanics well for a variety of experimental conditions [3, 15]. The static nonlinearity of the Hammerstein system is very similar to a half-wave rectifier under stationary conditions [35].



Figure 2.9: Parallel-cascade model of joint mechanics

The procedure used under stationary conditions to identify the parallel-cascade model from the position and torque data records will be briefly outlined below [3]:

- Intrinsic stiffness is estimated by identifying the IRF of the linear pathway from the position and torque signals. Since the reflex response has a delay, the IRF length is fixed to the delay associated with the reflex mechanisms to eliminate the possibility of reflex contamination.
- 2) The intrinsic torque is estimated by convolving the position with the model obtained in Step 1. The intrinsic residual torque is computed.
- A Hammerstein system is estimated between the differentiated position (velocity) and the intrinsic residual torque from Step 2.
- 4) The reflex torque is estimated by convolving velocity with the model obtained in Step 3. The reflex residual torque is computed.
- 5) The total predicted torque is calculated as the sum of the estimated intrinsic and reflex torques. The percentage variance accounted for is computed between the actual and predicted total torques.
- 6) Using the reflex residual torque from Step 4 instead of total torque, the procedure starting from Step 1 is repeated. Iterations will continue until the percentage variance accounted for by the model fails to increase.

Some steps must be explained in more detail. The reflex torque response is known to have a delay, which justifies limiting the IRF length in Step 1 to only allow intrinsic mechanisms to be identified. Intrinsic mechanisms occur at short latencies, so this step will not prevent full characterization of the intrinsic dynamics. The intrinsic and reflex torques are considered to add linearly for simplicity, however in reality the interactions are likely to be complex and nonlinear. The iterative procedure improved estimates by removing components of the output signal which were not modeled by the pathway being estimated. Using the torque residuals with each iteration in effect increased the signal-tonoise ratio (SNR).

The parallel-cascade model of joint mechanics appropriately represents ankle joint mechanics for a number of reasons. The dynamics that are estimated from the reflex pathway are consistent with the velocity sensitivity of the reflex mechanisms and the low-pass characteristics of muscle activation dynamics. Also the shape of the estimated reflex
stiffness IRF using the parallel-cascade model is very similar to the reflex torque response to a pulse displacement. In particular, GS reflex behaviour has been shown to be strongly non-linear. The response of the GS to a pulse depends in a non-linear fashion on amplitude, direction and duration of the pulse, as well as the level of voluntary activation [35]. Therefore the assumption of a delayed, non-linear pathway with low-pass dynamics is reasonable for reflex stiffness.

The intrinsic pathway represents the elastic, viscous and inertial properties of the joint. The estimated intrinsic stiffness is found to account for much of the torque VAF when there is no or little reflex activity (as seen in the GS EMG), which demonstrates that the linear pathway is a suitable description of intrinsic stiffness under stationary conditions. The parallel-cascade model has been successful under postural conditions but it is important to recognize that during non-stationary situations this model may no longer represent ankle joint dynamics well.

2.4.3 Time-Varying Techniques

Reflexes are often studied under static conditions, because the identification procedures are simplified when using time-invariant solutions. Although there are many reliable techniques to identify linear time-invariant systems, the majority of biological systems are nonlinear and have time-varying behaviour. Thus the use of time-varying identification techniques allows a deeper understanding of physiological systems.

In general, there are four major categories of time-varying identification techniques: quasi-stationary methods, temporal expansion methods, adaptive methods, and ensemble methods [33]. Quasi-stationary methods apply time-invariant identification techniques provided the operating point does not change significantly over a time period comparable to the system's dynamics duration. For temporal expansion methods, the time-varying parameters (for a parametric model) or time-varying kernels (for a nonparametric model) are expressed as a linear combination of known time functions [33]. During identification, the coefficients of these linear combinations are estimated. A disadvantage of the temporal expansion method is that the form of the system's time-variation must be known in advance [33]. Adaptive methods utilize iterative algorithms that estimate model parameters whenever new data becomes available, and work well for

slowly time-varying systems. However the system's structure must be known *a priori* [33].

Ensemble methods are capable of identifying very rapidly changing systems, those in which the changes in the dynamics occur faster than the duration of the dynamics themselves, and require no *a priori* knowledge about the time-variation structure [33]. A model of the system is generated at every instant in time during the time-varying behaviour using an ensemble of input-output realizations. The input-output relationship is evaluated across the ensemble at specific instants rather than across time. The time-varying behaviour is assumed to be the same for each realization.

2.4.3.1 Techniques used to study Joint Dynamics

The pioneer in ensemble-based time-varying studies examining joint dynamics was Soechting and colleagues who used a correlation-based approach to study the human elbow's myotatic response [36] and dynamic compliance [37]. However this time-varying identification technique imposed severe restrictions on the experimental protocol as the timing between the input signal and the onset of time-varying behaviour had to be controlled precisely.

Time-varying identification approaches based on parametric models have been used to study joint dynamics during movement. Parametric models can be very useful because the estimated parameters have physical meaning and allow direct inferences into motor control [38]. A recent ensemble time-varying technique used position perturbations as input to a linear, time-varying, second-order model of joint stiffness and the perturbation torque as output [38]. With multiple trials, a set of linear equations was formed and the parameters as a function of time were solved for using standard least squares estimation. Filtering techniques were used to extract accurate estimates of the position perturbations from the angular measurement that included the voluntary movement [38]. Most other ensemble techniques align the trials based on a feature in the movement to obtain an ensemble averaged movement which is then subtracted from each trial to obtain the desired perturbations.

However, a major limitation of these parametric techniques [36-38], is that the instantaneous dynamics were assumed to be well modeled by a linear, second order

system. If this assumption is incorrect for the time-varying behaviour studied, the results will be meaningless. A recent algorithm for estimation of time-varying impulse response functions was created using autoregressive moving average (ARMA) models, but was applied to study renal blood pressure and flow [39]. Although the model order was not required *a priori*, the form of the models were still restricted to the AR and MA types. Nonparametric identification techniques do not require the assumption of a model structure or order before hand and can identify structures that may change in time.

In our laboratory, the nonparametric approach for time-varying identification of joint dynamics was pursued using ensemble methods. MacNeil and colleagues [33] utilized ensemble input-output data to obtain least-squares estimates of linear, time-varying impulse response functions by applying singular value decomposition. MacNeil's technique was used in two separate experimental paradigms: a rapid contraction change [40] and a rapid imposed movement [41]. The stretch reflex EMG dynamics were found relating joint velocity to EMG at a temporal resolution equal to the sampling rate. The development of ensemble techniques in our laboratory will be discussed in more detail in the following section.

2.4.4 Time-Varying Identification Ensemble Methods

The ensemble method was chosen as the time-varying technique for ankle stiffness identification over other methods for several reasons. First, ensemble methods are capable of identifying very rapidly changing systems. Secondly, they require no a priori knowledge about the time-variation structure [33]. Generally they apply standard time-invariant techniques, but to the input-output data across the ensemble at specific points in time.

The main disadvantage with ensemble techniques is that a large number of realizations must be obtained where the system's behaviour from one realization to the next does not change, making the experimental methodology cumbersome. The more similar realizations obtained, the better the model's parameters can be estimated as they are estimated across the ensemble rather than across time. The number of data points (i.e. number of trials) should be much larger than the number of model parameters estimated (i.e. IRF length) to obtain reliable estimates.

Using ensemble methods, a model of the system is generated at every instant in time during the time-varying behaviour from an ensemble of input-output realizations, as shown in Fig. 2.10. The input-output relationship is estimated across the ensemble (i.e. each column in the input and output matrices of Fig. 2.10 represents a realization) at specific instants (i.e. each row in the input, output and IRF matrices of Fig. 2.10 represents an instant in time). The time-varying behaviour is assumed to be the same for each realization.



Figure 2.10: Input-Output matrices and the time-varying IRF matrix from the time-varying convolution integral generated using ensemble methods

As introduced in the previous section, MacNeil et al created a linear, time-varying identification method using ensemble data [32]. The time-varying convolution integral is manipulated to obtain a set of linear equations, each representing a realization from the ensemble data. These equations in matrix form represent the output at time *i* expressed as weighted sums of past, present and future input values. The least-squares solution to the matrix equation provides estimates of the time-varying IRFs (or weighting functions) and is obtained by applying singular value decomposition. This technique places no restrictions on the timing between the input and time-varying behaviour, unlike previous ensemble techniques [36, 37]. However, it was found to estimate less reliably with

coloured inputs and low output signal-to-noise ratios (SNR). Therefore a new nonparametric technique was developed to address these two issues.

2.4.4.1 Linear Pseudoinverse Technique

Lortie and Kearney proposed a new nonparametric technique to identify linear, time-varying systems from ensemble data [42]. At each sampling time, a matrix equation involving estimates of the input autocorrelation and input-output cross correlation functions is computed from data across the ensemble. The matrix inverse needed to solve the equation is replaced with a pseudoinverse, which has been found to provide more reliable estimates when the input is coloured and the output SNR is low [43, 44]. Thus the basic correlation approach in combination with the pseudoinverse approach was extended by Lortie and Kearney in this new technique.

2.4.4.2 Hammerstein System Technique

A new technique to identify time-varying Hammerstein systems from ensemble data was also designed [45]. A correlation approach is first used to obtain initial estimates of the linear subsystem parameters at every sample time. A two step iterative optimization algorithm is then employed to produce final estimates of the system parameters. The first process in the iterative optimization algorithm involves fixing the linear subsystem parameter estimates and finding the estimates of the nonlinear subsystem parameters that minimizes the sum of squared differences between the observed outputs and the outputs predicted by the Hammerstein model. During the second process, the subsystems are reversed; the nonlinear subsystem parameters are fixed while the linear subsystem parameters are found. This two-step procedure is repeated until the sum of the squared differences between the observed and predicted outputs fails to decrease. The optimization algorithm then repeats at the subsequent sampling times. The static nonlinearity is assumed to be represented by a polynomial at each time instant, with a maximum polynomial order that is chosen prior to identification.

The advantage of both the linear and Hammerstein techniques is that they are capable of identifying the dynamics at time intervals equal to the sampling rate, providing excellent resolution of the dynamics across a time-varying behaviour.

2.4.4.3 Previous Validation

Both techniques were tested separately with simulated data, as the algorithms were not yet combined into the parallel-cascade model. A linear, time-varying system simulated the intrinsic compliance of the ankle during a rapid dorsiflexing movement over a typical range of motion [4]. This was done by dividing the motion of the ankle into equally spaced positions corresponding to a given sampling time. The inertial (I), viscous (B) and elastic (K) parameters from the second order model of intrinsic compliance (see Section 4.3.1, Equation 4.3) were found by interpolating between parameter values at corresponding joint positions using data from actual experiments performed under quasistationary conditions. A block diagram of the procedure can be seen in Fig. 2.11.



Figure 2.11: Block diagram of Lortie's simulation [4]

The simulation studies tested the linear, pseudoinverse time-varying identification technique for a variety of input bandwidths and output noise conditions. The mean variances accounted for, VAF_{IRF} (see Section 4.4.2, Equation 4.6), between the true and predicted systems are shown in Fig. 2.12. Fig. 2.12B shows the effect of changing the cut-off frequency of the filter used to generate the position inputs at a set output SNR of 5 dB. Fig. 2.12A shows the effect of changing the noise conditions at the output while using the same input filter cut-off frequency of 10 Hz. Clearly the results showed a significant improvement over MacNeil's least-squares technique when the inputs are colored and the

output SNR is low, and proved the validity of the technique for identifying the linear, intrinsic pathway of ankle stiffness.



Figure 2.12: Mean VAF between true and estimated IRFs as a function of input filter cutoff frequency (B) and of output SNR (A) from Lortie's simulation [4]

To test the time-varying Hammerstein technique, a similar simulation was used to generate ensemble data representing the reflex stiffness pathway [4]. The procedure was nearly identical to that illustrated in Fig. 2.11, however the values of reflex gain (*G*), damping parameter (ζ) and natural frequency (ω_n) from the second-order model of reflex stiffness (see Section 4.3.1, Equation 4.4) were those found by interpolation from experimental data. This first simulation study provided clear evidence of the techniques strong estimation capabilities even in the presence of significant output noise and fewer realizations, as illustrated by the variance accounted for plotted in Fig. 2.13.



Figure 2.13: Mean VAF between true and estimated static nonlinearities (A) and between true and estimated IRFs (B) as a function of output SNR using three different ensemble sizes from Lortie's simulation [4]

A second simulated system was created to test the conditions when the static nonlinearity changes in time and when abrupt changes occur in the static nonlinearity and/or the linear dynamics [4]. The results demonstrated that the technique performs very well when the static nonlinearity varies with time. The abrupt changes caused very small drops in the VAF between the true and estimated IRFs and SNLs, however did not hinder the identification's ability of identifying the dynamics, as the drops in VAF were in fact caused by the downsampling of the simulated output signals prior to the identification.

2.5 Objectives

The main objective of this thesis work was to use recently developed time-varying identification algorithms to extend the parallel-cascade model to time-varying conditions. The identification technique was then to be tested in two ways:

- Using simulated data, representing time-varying ankle stiffness behaviour; and
- Using experimental time-varying data obtained during an imposed ramp movement.

The simulation study allowed the validation of the algorithm by comparing the true and identified systems and outputs. The experimental study tested the technique's capabilities with real data.

2.5.1 Motivation

With a robust time-varying identification technique, our laboratory will be able to examine a variety of time-varying behaviours and provide insight into the role of peripheral mechanisms. Ideally, this novel algorithm will be used to study voluntary movement, and the results will contribute to our understanding of the mechanical consequences of the stretch reflex during movement.

Beyond basic motor control research, there is the possibility to explore neuromuscular disorders, such as cerebral palsy, Parkinson's disease, and spinal cord injuries, using these quantitative tools. People with neuromuscular disorders have varying degrees of joint stiffness or muscle tone (spasticity), and it is currently assessed qualitatively. Quantitative tools may be extremely useful for assisting in the diagnosis and management of the disease.

The application of joint mechanics studies have far-reaching effects into a variety of fields such as: rehabilitation [46], prosthetics [1], and robotics [47]. Functional electrical stimulation (FES), which restores function to paralyzed muscles by electrical stimulus, requires information about joint dynamics for control programs to maintain joint stability over a range of muscle activation levels [1, 46]. The design of prosthetic limbs is greatly enhanced if the dynamics of the prosthesis match closely the limb they replace [1]. Robotics will also benefit from research done on human joint dynamics, as the neuromuscular control system may provide useful insight into the design of robotic control [1, 47].

3. Experimental Apparatus

This chapter describes the experimental setup used to acquire ankle stiffness data, providing details on the electrohydraulic actuator, custom-fit boot, transducers, control system, data acquisition, and visual display. Fig. 3.1 is a general depiction of the experimental apparatus and the signal flow. The subject lay supine on the bed with their left foot attached to the foot pedal of the actuator via a low-inertia, custom-made fibreglass boot. A strap over the lower thigh maintained the knee angle and sandbags under the knee provided support. An LCD monitor mounted above the subject's head provided visual feedback. A servo valve controlled the flow of hydraulic fluid to the actuator. The actuator was controlled by proportional position feedback implemented with an xPC real-time digital signal processing system. Position, torque, gastrocnemius EMG, tibialis anterior EMG and input perturbation signals were digitized and stored on the workstation. The major components will be discussed in detail below.



Figure 3.1: Experimental apparatus and signals

3.1 Electrohydraulic Actuator

A rotary hydraulic motor (ROTAC 26R-5) was controlled by a two-stage electrohydraulic servo-valve (Moog 730-233). To minimize backlash, the actuator shaft was coupled directly to the boot fixation assembly. The axis of rotation of the actuator assembly was aligned with the ankle's axis of rotation, as described in Section 3.2.2.

Three safety mechanisms ensured that the subject's ankle was not moved beyond its comfortable range of motion (ROM). First, there were adjustable mechanical stops (steel bolts), labelled in Fig. 3.2, fixed to the torque transducer support. The bolts would contact a piece attached to the rotating shaft at the limits of ROM. Second, there was an adjustable hydraulic cam that automatically stopped hydraulic flow to the actuator upon reaching the limits of the ROM. Both the mechanical stops and hydraulic cam were adjusted to fit the subject's ROM prior to experiments being performed. These two safety mechanisms are completely independent systems, but are both activated by the rotating foot pedal. Third, the subject and experimenter each had buttons at hand that when pressed would immediately cut off the flow of the hydraulic fluid to the actuator.

3.2 Boot

The purpose of the custom-fit boot was to provide a rigid interface between the subject and the actuator and restrict movements to dorsiflexion and plantarflexion. The boot must have a low inertia so as to maximize the ankle's dynamic response, but provide strength and stability against the perturbations and subject. The boot making procedure is outlined in detail in the REKLAB manual [48]. Photographs of a boot mounted to the rotating foot pedal are shown in Fig. 3.2.



Figure 3.2: Custom-fit boot bolted to foot pedal

3.2.1 Materials and Construction

The boot was made of fibreglass orthopaedic casting tape (Dynacast). Each subject had the orthopaedic tape wrapped around their foot and ankle while maintaining approximately a 90 degree angle. The malleoli were marked on the cast for use in determining the axis of rotation. The casting material hardened slightly within about 10 minutes, and then was removed with a cast cutter. The boot then completely hardened overnight into a rigid mold of the subject's foot. The boot required trimming around the edges so that the subject could easily put the boot on and off. The toe region was also removed so that the subject could not generate torque with their toes. A 'tongue' for the boot was molded out of thermoplastic splinting material (Polyform A29215) between the boot and top of the foot, and was held in place during experiments with a Velcro strap.

3.2.2 Axis of Rotation

The approximate ankle axis of rotation with respect to anatomical landmarks was determined from anthropometric studies on human cadavers. This was 11 mm anterior and 12 mm distal to the lateral malleolus, as shown in Fig. A.1, and 1 mm posterior and 16 mm distal from the medial malleolus, as shown in Fig. A.2 [49]. The malleoli were marked on the boot, and we utilized these statistical average measurements to locate the axis of rotation. To fine-tune the axis location, the ankle was manually moved about the axis of rotation. Any movement at the knee would indicate a misalignment. In this case, the marks of the malleoli would be shifted until no movement occurred at the knee.

We then drilled holes at these locations (Fig. 3.2A) and placed the boot in a replica of the boot fixation assembly. Aluminium posts (Fig. 3.2B) were fixed onto the sides of the boot using steel-filled epoxy (Devcon), while being held in the boot fixation replica as if bolted on during experiments. A straight wire was placed through the axis of rotation of the ankle and that of the actuator, via the posts. The posts had holes drilled at the same height measured from the base of the foot pedal to the actuator center of rotation. After the epoxy hardened, the boot was ready for use.

3.3 Transducers

The signals required to study the neuromuscular control system using system identification are: angular position, torque and EMG. The sensors used to measure each of these signals will be discussed in turn.

3.3.1 Angular Position

A potentiometer (BI Technologies 6273) made of a plastic conductive material, was used to measure angular position of the foot pedal onto which the boot is bolted. A flexible helical beam coupling (McMaster-Carr 6208K51) was used to connect the potentiometer shaft to the shaft of the bearing mounted in one of the boot fixation supports, as shown in Fig. 3.2B. The coupling has six cuts to provide the necessary flexibility for parallel, angular and axial misalignment, up to a maximum of 0.1778 mm, 3° and 0.1270 mm, respectively. The maximum torque the coupling can handle is 0.7119 Nm, as opposed to a maximum start torque of 0.014 Nm needed by the potentiometer. It has zero backlash (no slipping), which is ideal for this application as it requires frequent starts and stops.

A mechanical contact sweeps along the plastic surface of the potentiometer, producing an output voltage linearly related to the contact's rotational displacement. This potentiometer has a resistance range of 1 to 900 k Ω with a maximum non-linearity of ±0.5% over 5.943 rad (340°). A custom-built potentiometer module was used to provide amplification and DC offset; it was calibrated to a sensitivity of 10 V/rad (or 0.1 rad/V). To estimate the resolution of the potentiometer and module, the noise was measured using a multimeter (Fluke 80) which recorded the output over a bandwidth of 200 kHz while shorting the input of the module to ground [50]. The resulting root-mean-square noise level was found to be 1.0 mV (or 0.0001 rad) [50].

3.3.2 Torque

To measure the torque produced by a subject, a general purpose reaction torque transducer (Lebow 2110-5K) was mounted via a flange to the second boot fixation support, as illustrated in Fig. 3.2. It is capable of measuring up to 565 Nm with a maximum nonlinearity of $\pm 0.1\%$ and has a high torsional stiffness of 103,941 Nm/rad. The stiffness of the human ankle is in the range of hundreds of Nm/rad or less (i.e. 200 Nm/rad) [51], smaller than the sensor's stiffness by a factor of roughly 1000. Since the ankle is significantly more compliant than the sensor, torque generated by the subject does not translate into torsional effects at the sensor, thus improving the sensitivity and accuracy of the measurement. Other advantages of the transducer were that it has minimal friction error, low end sensitivity due to the absence of moving parts and a high resistance to bending moments.

A custom-built torque transducer module provided gain and offset to the torque signal, and was calibrated to provide a sensitivity of 0.05 V/Nm (or 20 Nm/V). Following the same procedure to measure noise levels in Section 3.3.1, the RMS noise level for the torque transducer and module were measured to be 2.1 mV (or 0.042 Nm) [50].

3.3.3 Electromyography (EMG)

Electromyographic (EMG) signals were recorded from the gastrocnemius-soleus group (GS) and the tibialis anterior (TA), using a Delsys Bagnoli-4 EMG system. The Delsys system was well suited to our needs because:

- The Delsys electrodes have an 'active' electrode design which provides EMG measurements with a high signal-to-noise ratio (SNR), and;
- The belt-mounted interface and minimal amount of skin preparation made this system versatile and convenient, to accommodate the growing capacity of our laboratory.

The EMG system is composed of the electrodes (DE-2.1), main amplifier unit, and a beltmounted interface unit as shown in Fig. 3.3 and detailed below.



Figure 3.3: EMG setup [adapted from 52]

3.3.3.1 Electrodes

The Delsys DE-2.1 electrodes are active differential electrodes which have a unique design comprising two parallel bars in a bipolar configuration and a differential amplifier housed within the small electrode itself, as shown in Fig. 3.4. The signals are subtracted and pre-amplified (gain of 10) before being sent to the main amplifier unit. These electrodes have a common-mode rejection ratio (CMRR) greater than 80 dB, at 60Hz.



Figure 3.4: DE-2.1 single differential electrode design [52]. The EMG measurement is the potential difference between v_1 and v_2 .

The electrodes were applied to the muscles, after shaving and lightly rubbing with alcohol, and held in place with double sided adhesive tape. The parallel bars of the electrode must be placed perpendicular to the muscle fibre orientation. The electrode housing was labelled with an arrow which should point in the direction of the muscle fibres. The electrode for the GS was placed on the lateral head of the muscle and the electrode for the TA was placed on the belly of the muscle, approximately one third of the distance between the knee cap and the lateral malleolus, as shown in Fig. 3.5. A reference, or neutral, electrode was attached to an electrically neutral location on the body (i.e. the patella) and all EMG signals were measured with respect to this electrode.



Figure 3.5: Electrode Locations

3.3.3.2 Main amplifier and interface unit

The EMG and reference cables were plugged into a belt-mounted unit. The interface unit I/O cable sends the signals from the belt-mounted unit to the main amplifier unit. This main amplifier unit supplies power to the electrodes, receives and conditions the signals and provides four outputs for signal acquisition. Patient safety was insured by the use of an isolated medical grade power supply. Isolation was achieved with an isolated transformer. The supply provides a regulated 12 V output and conforms to the medical IEC60601 standard. This wall mounted supply has leakage currents of less than 10 μ A and is safety isolated to 3750 V_{RMS} [52].

The main amplifier unit has individual gain switches for each channel, as well as two LEDs to detect signal saturation (\pm 4.8V) and line interference (60 Hz) on each channel. Four BNC sockets are used to connect the output signals to the data acquisition card.

The entire system (electrodes, interface unit and main amplifier) was tested using a custom-built in-house circuit that attenuated a single-ended input and converted it to a differential signal [53]. The input to the circuit was a swept sine wave from high to low frequencies over the range 1 Hz – 10 kHz generated using a dynamic signal analyzer (HP 3562A). The output from the EMG channel of the main amplifier was recorded on the dynamic signal analyzer. Subsequently the system's transfer function was computed and plotted between the input to the electrode and the measured main amplifier output at each input frequency. Fig. 3.6 shows the system's frequency response at a gain of 80 dB, with a bandwidth of approximately 22.4 Hz – 2.04 kHz. The circle marks the -3 dB point from the steady gain of 80 dB and occurred at a cut-off frequency of 22.4 Hz. The pointer trace on the analyzer was similarly used to find the high cut-off frequency. The channel was tested at its different gain settings and the system was shown to have the expected bandwidth of 20-2000 Hz, at the overall amplification settings of 40, 60 and 80 dB (100, 1000, 10,000 V/V). The physiological bandwidth of EMG signals, as presented in Section 2.2.7, lies well within the usable frequency range of this detecting system.



Figure 3.6: Frequency response, gain (upper plot) and phase (lower plot), between input to electrode and output from one EMG channel at a gain of 80 dB using an in-house circuit and dynamic signal analyzer [53]

3.4 Experimental Control

Experimental and analytical tools were developed and implemented using MATLAB (The Mathworks Inc., Natick, MA). A graphical user interface (GUI) recently developed by Przemek Bock [54], running under Windows XP, controlled the experiments.

3.4.1 Servo Control System

The desired position input was generated digitally and output to the servo-valve using a 6-channel, 16-bit digital-to-analog (D/A) converter (ComputerBoards Inc., PCIM-DDA06/16). The controller was developed in Simulink (MATLAB) and used the xPC real-time digital signal processing (DSP) system. The xPC system requires a host PC running MATLAB/Simulink and the target PC running a real-time kernel. The host computer loads the DSP code to the target computer via Ethernet.

Position and torque signals used by the Simulink controller were first anti-alias filtered at 400 Hz with an 8-pole, 6-zero, linear-phase, constant-delay, low pass Bessel filter (Frequency Devices 9064) before being sampled at 1 kHz by the target computer using a 8-channel, 16-bit analog-to-digital (A/D) converter (ComputerBoards Inc., PCIM-DAS1602/16).

The controller used proportional position feedback for the actuator. This controller used only the position error signal to drive the actuator so the effects on the actuator position from torques generated by the subject were insignificant. Under position control, the foot pedal felt very stiff to the subject; it provided stiffness greater than 7,325 Nm/rad. This value was measured as the steady-state stiffness of the system in proportional control [50]. The actuator frequency response under proportional control with no subject is illustrated in Fig. 3.7. This response was generated using a dynamic signal analyzer (HP 3562A), which applied random perturbations with a bandwidth of 0.5 - 500 Hz to the actuator, measured the corresponding position signal, and computed the frequency response [55]. This system is capable of applying inputs up to approximately 60 Hz, which is sufficiently high to identify ankle dynamics.



Figure 3.7: Gain, phase, and coherence of the transfer function between input perturbation and position under proportional control mode with no subject [55]

3.5 Data Acquisition

The position, torque, EMG and input position data were sampled using a dynamic signal acquisition card (National Instruments 4472) on the host computer. This card has a built-in digital anti-aliasing filter, with an extremely sharp cut-off frequency of approximately 0.4863 times the sample rate. We used a sampling rate of 1 kHz, thus the anti-aliasing filter has a cut-off of 486.3 Hz. The sampled data was stored on the host computer.

3.6 Visual Feedback

An LCD monitor hung above the subject's head and was capable of displaying two feedback signals via one target symbol that could be plotted along two axes. Fig. 3.8 shows the actual display with the square target. Plot A displays only one feedback signal plotted on the vertical axis. Plot B depicts the target with two feedback signals, one plotted on the vertical axis and the other on the horizontal axis. The visual goal for the subject can vary depending on the task and the feedback signals, but for illustration purposes Plots C and D show an attempt to minimize both signals to zero (i.e. between the dotted lines on the vertical axis, as shown in C, and to the left on the horizontal axis, as shown in D). In the experiments for this thesis, a single feedback signal of the error between the target torque and the low-pass filtered torque was plotted along the vertical axis, and subjects were asked to minimize the signal to zero.



Figure 3.8: Examples of Visual feedback to the subject

In a method created by Ross Wagner, the digital feedback signals were sent from the Simulink model via a User Datagram Protocol (UDP) driver block to a second computer. This feedback display computer created the graphical display as shown in Fig. 3.8. The video signal was then sent to the LCD monitor to provide the visual feedback to the subject.

4. Validation of the Time-Varying, Parallel-Cascade Identification Algorithm

This chapter presents the novel time-varying, parallel-cascade identification algorithm. First, the iterative identification procedure is described in detail. The next section describes the simulation model used to generate ensemble data for testing the algorithm. A time-varying system meant to represent ankle joint stiffness was created based on previous results obtained under stationary conditions. Computer-generated and experimentally measured position input records were passed through the simulated system to generate time-varying ensemble data. This data was then used to test the algorithm's ability to estimate the two components of stiffness. The simulation results, including the comparison of the true and estimated systems, are presented in the subsequent section. The chapter concludes with a discussion of the ability of the timevarying techniques to estimate the simulated system dynamics.

4.1 Identification of Time-Varying Joint Stiffness

The main goal of this thesis was to develop and validate a method for the identification of time-varying intrinsic and reflex mechanisms. The two time-varying techniques presented in Section 2.4.4 were incorporated into a time-varying, parallel-cascade identification algorithm, which is described in detail in this section.

Many different algorithms could be considered for the time-varying identification of ankle joint mechanics, as presented in Sections 2.4.3 - 2.4.4. Currently the methods developed in our lab were chosen as most suitable for the parallel-cascade model. One of our major assumptions is the use of the parallel-cascade model representing ankle joint mechanics during the imposed movement.

The parallel-cascade model, presented in Section 2.4.2, is shown in Fig. 4.1; the upper pathway represents intrinsic stiffness as a linear dynamic system and the lower pathway represents reflex stiffness as a nonlinear dynamic Hammerstein system. The overall torque is assumed to be the linear summation of the torques due to intrinsic (TQ_I) and reflex (TQ_R) mechanisms.



Figure 4.1: Parallel-cascade model of joint mechanics

Fig. 4.2 illustrates the signals and systems generated using the time-varying, parallel-cascade identification algorithm from ensemble data. The implementation details of the algorithm are explained further in Appendix B, and the MATLAB program is given in Appendix C.

Before describing Fig. 4.2 in more detail, equations for the percentage variance accounted for (%*VAF*) using ensemble data are presented. The %*VAF* between an actual (X) and predicted (\hat{X}) signal or system at each time t was calculated as:

$$\% VAF_{X}(t) = 100 \left(1 - \frac{\operatorname{var}(X_{N}(t) - \hat{X}_{N}(t))}{\operatorname{var}(X_{N}(t))} \right), \tag{4.1}$$

where the variances were computed across the ensemble with *t* held constant. Subsequent references to this %VAF will be shown as either $VAF_X(t)$ or VAF_X , since the majority of the calculations were done across the ensemble.

The %VAF corresponding to each realization N was computed as:

$$\% VAF_{X}(N) = 100 \left(1 - \frac{\operatorname{var}(X_{N}(t) - \hat{X}_{N}(t))}{\operatorname{var}(X_{N}(t))} \right), \tag{4.2}$$

where the variances were estimated using data across time and N held constant. Subsequent references to this % VAF will be shown as $VAF_X(N)$.



Figure 4.2: The parallel-cascade structure used to estimate time-varying intrinsic and reflex stiffness. The solid, dark curves represent experimental data and the dotted, light curves represent predicted data. All systems are defined explicitly as a function of time (t) and lag (τ). The signals are explicitly defined as a function of time (t) and realization (N) to represent ensemble data. Similarly, for each signal the two curves with dots in between represent ensemble data.

The identification procedure can be outlined as follows, referring to Fig. 4.2:

1) Intrinsic dynamics, $P\hat{T}Q_{IRF}(t,\tau)$, were estimated using the linear, pseudoinverse technique between the position, P(t,N), and torque, TQ(t,N), ensemble data. The lengths of IRFs were limited to the delay associated with the reflex mechanisms. To estimate the inverse of intrinsic stiffness (intrinsic compliance, $T\hat{Q}P_{IRF}(t,\tau)$), a noise-free torque was obtained by convolving a white position input with $P\hat{T}Q_{IRF}(t,\tau)$. Subsequently $T\hat{Q}P_{IRF}(t,\tau)$ was estimated using the linear, pseudoinverse technique between the noise-free torque and position. 2) The position ensemble was convolved, using time-varying convolution, with $P\hat{T}Q_{IRF}(t,\tau)$ from Step 1, to predict the intrinsic torque, $\hat{T}Q_{I}(t,N)$. The intrinsic residual torque for each realization (*N*) was computed as:

$$\hat{T}Q_{IR}(t,N) = TQ(t,N) - \hat{T}Q_{I}(t,N),$$
(4.3)

and used as an estimate of the reflex torque.

- 3) Reflex dynamics were estimated, using the time-varying Hammerstein technique, between joint velocities, V(t,N), and intrinsic residual torques, $\hat{TQ}_{IR}(t,N)$.
- 4) The outputs of the static nonlinearities, $V^+(t,N)$, were convolved with $V\hat{T}Q_{IRF}(t,\tau)$ (the linear subsystems obtained in Step 3) to predict the reflex torques, $\hat{T}Q_R(t,N)$. The reflex residual torque for each realization (N) was computed as:

$$\hat{T}Q_{RR}(t,N) = TQ(t,N) - \hat{T}Q_{RI}(t,N), \qquad (4.4)$$

and used as a new estimate of the intrinsic torque.

5) The net predicted torque for each realization (*N*) was computed as:

$$\hat{T}Q(t,N) = \hat{T}Q_I(t,N) + \hat{T}Q_R(t,N), \qquad (4.5)$$

The $VAF_{TQ}(t)$ was computed between the actual and predicted net torques at each time *t* as per equation 4.1.

6) The procedure was repeated starting from Step 1, using $\hat{T}Q_{RR}(t,N)$ from Step 4 in place of TQ(t,N). Iterations continued until the improvement in the mean $VAF_{TQ}(t)$ was less than 0.01.

4.1.1 Algorithm Details

Prior to initiating the procedure outlined above, the mean position and mean torque across the ensemble were calculated and removed from all realizations. Thus the position records consisted of only the perturbations suitable for identification. The identification techniques make the assumption that the inputs have a zero mean, which is ensured when removing the ensemble mean.

The frequency band of interest for stiffness is low, particularly for the reflex component. Position and torque must be sampled at a high rate to capture the reflex delay. There is little power at high frequencies in the output and input, thus the system estimates contain noise at higher frequencies. Therefore these systems (intrinsic compliance and reflex stiffness) were low-pass filtered to remove the high-frequency content, using a 3-point moving average algorithm, prior to convolution with their inputs.

4.1.1.1 Hammerstein details

The static nonlinearities (SNLs) were assumed to be represented by polynomials, with coefficients $p_0(t)$, $p_1(t)$, $p_2(t)$... $p_n(t)$ at each time *t* according to:

$$g(t, u(t-\tau)) = p_0(t) + p_1(t)u(t-\tau)^1 + p_2(t)u(t-\tau)^2 + \dots + p_n(t)u(t-\tau)^n, \qquad (4.6)$$

where $g(t, u(t-\tau))$ is the time-varying nonlinear mapping function and $u(t-\tau)$ is the input velocity. The maximum polynomial order (*n*) must be defined prior to identification. Throughout this thesis, the maximum polynomial order was set to three.

The overall gain of the Hammerstein system is determined by the gain of the static nonlinearity and that of the linear dynamics. When estimating a Hammerstein system it is not possible to determine the distribution of gains between the static nonlinearity and linear dynamics [4]. Thus, the Hammerstein systems must be normalized to permit comparisons between different Hammerstein systems.

Normalization was achieved by manipulating the gain distribution such that the DC gain of the linear system was unity. To achieve this, a correction factor was calculated as the area under the IRF at each point in time. The IRFs were then divided by the correction factor and the polynomial coefficients multiplied by it at the corresponding times. This resulted in the gain being redistributed between the two subsystems so that the area under the IRF was unity at every instant while the overall gain of the Hammerstein system remained unchanged.

4.1.1.2 IRF Propagation

The time-varying, parallel-cascade identification algorithm uses a correlation approach to estimate the linear dynamics. To estimate a linear, time-varying system using this approach, a matrix equation is solved in which the input-output crosscorrelation function estimate is expressed in terms of the input autocorrelation function estimate and the system weighting function [56]. As a result, IRFs cannot be estimated at times shorter than the IRF length and so were set to zero. The equations involved in the basic correlation approach will be briefly outlined, to understand why this occurs.

Given an ensemble of realizations, the discrete time convolution integral for the N^{th} realization can be represented as:

$$y_N(t) = \Delta t \sum_{\tau=M1}^{M2} h(t,\tau) u_N(t-\tau), \qquad (4.7)$$

where *M1* and *M2* represent the finite length of the 2-sided time-varying weighting function $h(t,\tau)$, where $h(t,\tau) = 0$ for lags $\tau < M1$ and $\tau > M2$.

If both sides are multiplied be $u_N(t-k)$, summed over all realizations (N = 1 to R, where R is the total number of realizations), and multiplied by 1/R, the result will be:

$$\frac{1}{R}\sum_{N=1}^{R}y_{N}(t)u_{N}(t-k) = \Delta t\sum_{\tau=M1}^{M2}h(t,\tau)\frac{1}{R}\sum_{N=1}^{R}u_{N}(t-\tau)u_{N}(t-k), \qquad (4.8)$$

where *k* ranges from *M1* to *M2*.

Equation 4.8 can be rewritten in terms of correlation estimates, as follows:

$$\hat{\phi}_{yu}(t,-k) = \Delta t \sum_{\tau=M1}^{M2} h(t,\tau) \cdot \hat{\phi}_{uu}(t-k,k-\tau), \qquad (4.9)$$

where $\hat{\phi}_{yu}(t,-k)$ is the time-dependent, input-output, cross-correlation function estimate and $\hat{\phi}_{uu}(t-k,k-\tau)$ is the time-dependent, input autocorrelation function estimate.

It is evident from Equations 4.8 and 4.9, that the matrix solution requires the use of inputs at past times, i.e. $u_N(t-k)$ where k ranges from M1 to M2. Therefore the estimation of $h(t,\tau)$ will begin at time t, but requires input data at times t-M1 and t+M2. Recall that M1 and M2 represent the length of a 2-sided IRF. Thus, although the acquired data may be L in length, the IRFs of a 2-sided (anti-causal) system cannot be estimated for the first M1 and last M2 time points and so are set to zero. Thus the system can only be estimated for L - (M1+M2) time points. Similarly for a 1-sided (causal) IRF with the length limited from 0 to M1 (range of k), the IRFs for the first M1 time points must be set to zero. Since the correlation approach requires past inputs at times equivalent to the IRF length and does not estimate IRFs at these time points, there are two important considerations for the user. To describe the time-varying behaviour, IRFs must be estimated at all time points throughout the behaviour. Therefore given that initial and final IRFs are set to zero, it is important to sample enough data prior to and after the end of the time-varying behaviour. Secondly, the IRF lengths must be chosen carefully, as their length not only affects the quality of the estimated systems but also the times for which IRFs cannot be estimated.

The parallel-cascade identification algorithm predicts the torques generated from each pathway and uses updated torque records (residual torques in Steps 2 and 4) with each iteration to improve the estimated systems. If IRFs are not estimated at the specified times, then clearly torques cannot be predicted at these times. If the identification procedure continued, including the zero IRFs, the amount of usable data would decrease with each iteration of the parallel-cascade procedure, because the residual torques would be based on erroneous predicted torques.

The solution we chose to mitigate this problem was to propagate the first non-zero IRF towards the start time (and end time for 2-sided IRFs). The rational behind this is the assumption that the system is time-invariant at these time points; that is they should occur well before and well after the time-varying behaviour is complete. Fig. 4.3 displays an intrinsic compliance IRF immediately after identification (A) and after propagating back the first non-zero IRF (B).



Figure 4.3: $T\hat{Q}P_{IRF}(t,\tau)$ immediately after identification (A) and after propagation of the first non-zero IRF (B). Notice that $T\hat{Q}P_{IRF}(t,\tau)$ (A) is set to zero for the first 200 ms (IRF length) along time axis.

4.2 Simulation

To test the new identification method, a realistic data set was generated by simulating a time-varying system representing how ankle joint stiffness might vary during a ramp movement. However, it is important to note that very little is known about the true dynamics during a plantarflexing movement and hence this simulation does not correspond to how stiffness dynamics actually change during movement. The simulation procedure is shown as a block diagram in Fig. 4.4 and will be described next.



Figure 4.4: Simulated Intrinsic and Reflex pathways

4.2.1. Simulated Time-Varying Systems

Models of intrinsic compliance and reflex stiffness dynamics of the ankle joint obtained for quasi-stationary conditions were used to create the simulated time-varying system. Intrinsic compliance, at time *t*, is well modeled by a linear second-order, low-pass system with transfer function:

$$TQP_{IRF}(s) = \frac{P(s)}{TQ_{I}(s)} = \frac{1}{I(t)s^{2} + B(t)s + K(t)},$$
(4.10)

where P is position, TQ_I is intrinsic torque, and I(t), B(t), and K(t) are time-dependent inertial, viscous, and elastic parameters, respectively [3]. The linear component of the Hammerstein system, at time t, is well modeled by a delay in series with a second-order, low-pass system with transfer function:

$$VTQ_{IRF}(s) = \frac{TQ_R(s)}{V^+(s)} = \frac{G_R(t)\omega_n^2}{(s^2 + 2\zeta(t)\omega_n(t)s + \omega_n(t)^2)},$$
(4.11)

where TQ_R is reflex torque, V^+ is the static nonlinearity velocity output, $G_R(t)$ is reflex gain, $\omega_n(t)$ is the second order natural frequency, and $\zeta(t)$ is the damping parameter [3].

The 2nd order parametric fits to intrinsic and reflex ankle stiffness models estimated in our laboratory during quasi-stationary conditions, were used to choose reasonable parameters for this simulation [57]. To simulate the ankle undergoing a

plantarflexing ramp, certain parameters were chosen to vary with time. Only the reflex gain, intrinsic elastic and viscous parameters underwent a ramp change. A previous study under stationary conditions demonstrated that these parameters showed a strong dependency on position, all values increasing as the foot was more dorsiflexed [57]. Moreover, the intrinsic inertial and reflex frequency and damping parameters were found to be position independent. Thus, the chosen parameter values are representative of normal values obtained for the ankle under stationary conditions.

The time-varying parameters decreased by 50% of their initial absolute value in a ramp change of 300 ms and each parameter change started at a different time, as shown in Fig. 4.5. The large change and staggered start times were chosen to make the time-varying behaviour more obvious. This system will be used to test the algorithm's ability to track a system with large changes occurring at different times. It is not expected that this will correspond to actual behaviour.

All signals and systems were simulated for an extra 500 ms prior to the start of the time-varying behaviour to account for start-up transients, when using the computergenerated position inputs. This extra time was not necessary when using the experimental inputs, since the input had been applied continuously to the ankle prior to data acquisition so there were no start-up transients. The data that was actually used for the identification was 2 s in length, taken after the first 500 ms. A sampling rate of 100 Hz was used.



Figure 4.5: Simulated Intrinsic (A,C,E) and Reflex (B,D,F) parameters. Note: the first 500 ms are not shown.

IRFs for $TQP_{IRF}(t,\tau)$ and $VTQ_{IRF}(t,\tau)$ as per Equations 4.10 and 4.11, were generated at each time instant using the parameters from Fig. 4.5. $PTQ_{IRF}(t,\tau)$ was determined by computing the dynamic inverse of $TQP_{IRF}(t,\tau)$ as follows. A torque input of Gaussian white noise (5 Nm in amplitude) was convolved with $TQP_{IRF}(t,\tau)$ to obtain position, over many realizations (see Fig. 4.4). This ensemble data was then used with the linear, pseudoinverse technique to estimate $PTQ_{IRF}(t,\tau)$ between the position input and torque output records.

The IRF lengths were 200 ms and 400 ms for $TQP_{IRF}(t,\tau)$ and $VTQ_{IRF}(t,\tau)$ respectively; these lengths allow the IRFs to die out. Intrinsic stiffness IRFs, $PTQ_{IRF}(t,\tau)$, were limited to 40 ms per side. The linear component of the Hammerstein system modeled the reflex delay by shifting $VTQ_{IRF}(t,\tau)$ by 40 ms. The simulation was run long enough to allow transient effects to die out. Only data after the end of the transient effects are presented in the results.

Simulations were performed with a number of position inputs. The input shown in Fig. 4.4 was Gaussian white noise passed through a first-order, low-pass Butterworth filter with a 30 Hz cut-off frequency. The results (next Section) are organized according to the input type and each input is presented along with the simulation outcomes.

The static nonlinearity of the Hammerstein nonlinear pathway was modeled as a third-order polynomial assumed to remain constant in time with coefficients p_0 , p_1 , p_2 , p_3 in the following equation:

$$y_N(t) = p_0 + p_1 u_N (t - \tau)^1 + p_2 u_N (t - \tau)^2 + p_3 u_N (t - \tau)^3, \qquad (4.12)$$

where u_N is the input velocity and y_N is the output of the static nonlinearity, for the N^{th} realization. The coefficients were found by fitting a third-order polynomial between the input velocity and half-wave rectified velocity. This was done because in time-invariant studies, the SNL has been found to resemble a half-wave rectifier. For both the simulated and estimated Hammerstein systems, the gain was distributed between the SNL and IRF such that the DC gain of the IRF was unity at every time.

Fig. 4.6 shows the simulated models. Note that $VTQ_{IRF}(t,\tau)$ were flat up until 40 ms across lag time corresponding to the reflex delay. The reflex stiffness (Fig. 4.6B) shows no variation across time because it was normalized to an IRF DC unity gain, whereas both $TQP_{IRF}(t,\tau)$ and SNL(t, V) display variation across time.

The simulated output was then generated as follows:

- i. Intrinsic torque $TQ_{I}(t,N)$ was simulated by convolving $PTQ_{IRF}(t,\tau)$ with its input position P(t,N).
- ii. Input position was differentiated to give velocity.
- iii. Velocity was passed through SNL(t, V) and then convolved with $VTQ_{IRF}(t, \tau)$ to generate $TQ_R(t, N)$.
- iv. The simulated net torque was calculated as, $TQ(t,N) = TQ_I(t,N) + TQ_R(t,N)$.



Figure 4.6: Simulated intrinsic compliance (A), reflex stiffness (B) and static nonlinearities (C). Note: the first 940 ms are not shown – longest IRF length (400ms) plus additional time (500ms) and reflex delay (40ms).

4.3 Results

Simulations were run using computer-generated Gaussian and pseudo-random binary sequence (PRBS), and PRBS experimental position input data. The simulation results are presented according to the type of position input used.

4.3.1 Gaussian Inputs

The computer-generated inputs were filtered to be more representative of actual experiments since the actuator itself acts as a filter. The previous simulations [4], discussed in Section 2.4.4.3, used Gaussian inputs, so it was expected that the identification techniques would work well with these signals.

A Gaussian input having a 10 Hz cut-off frequency (1st order Butterworth filter) and an amplitude of 0.025 rad was chosen so that the mean absolute velocity matched closely to that of the experimental input (Section 4.3.2). This input was chosen so that a substantial amount of torque would be accounted for by the reflex pathway, as it is known that a low mean, absolute velocity (such as that used in the experiments) yields larger reflexes. Inputs were generated randomly for 467 realizations (to be consistent with the number of realizations for the experimental input).

4.3.1.1 Simulated Signals

Some input-output realizations using this filtered Gaussian position input are shown in Fig. 4.7. The reflex torque (C) contributes about 1 to 5 Nm peak-to-peak of the total torque, whereas the intrinsic torque (D) contributes about 2 to 7 Nm peak-to-peak of the total torque.



Figure 4.7: Simulated position (A) and corresponding torque signals (B,C,D) from multiple realizations (the signals are offset vertically for clarity), using Gaussian position input (0.025 rad) low pass filtered to 10 Hz. Note: only 1 s of data is shown for clarity.

4.3.1.2 Model Evaluation

This sub-section probes the identification results and presents how well the model describes the data. The *VAF* between the total torque and predicted torques, $VAF_{TQ_x}(t)$, was calculated where $\hat{T}Q_x$ is the predicted torque based on the reflex stiffness, intrinsic stiffness or both (i.e. ' TQ_x ' is '*reflex*', '*intrinsic*' or '*total*'). These values define the amount of measured torque that can be attributed to the reflex, intrinsic or total stiffness model.

These *VAFs* are plotted across time in Fig. 4.8. Overall, the reflex pathway accounted for a mean of 26.0% of the total torque, and the intrinsic pathway accounted for a mean of 76.3% of the total torque, across time. The *VAF_{total}* is very high (mean 98.9%) throughout the simulated time-varying behaviour. However, the *VAF_{intrinsic}* starts

off around 70% and increases to about 85%, while VAF_{reflex} starts off at about 35% and decreases to 20%. This increase and decrease occurs simultaneously which is why the VAF_{total} does not change across time (total torque is the sum of the intrinsic and reflex torques).



Figure 4.8: *VAFs* between total torque and predicted torques, with the dashed lines indicating the start and stop of the respective parameter change (i.e. K₁G, B, as indicated in A). Note: the first 440 ms was neglected.
This significant change coincides with the lines indicating the ramp start and stop of the reflex gain parameter (G_s and G_e). Since the reflex gain decreased, the amount of reflex torque generated decreased. The total torque remained unchanged and thus the *VAF*_{intrinsic} increased and *VAF*_{reflex} decreased, since less torque was being attributed to the reflex model. The opposite trends are also evident for both the elastic parameter K and the viscous parameter B ramp changes, although much less pronounced. All the parameters changed by 50% of their initial value, but the elastic and viscous parameters were chosen somewhat conservatively as compared with actual experimental results. This was confirmed by running the simulation again, but only changing the elastic parameter from 300 to 150 Nm/rad (rather than 150 to 75 Nm/rad). The *VAF*_{intrinsic} did in fact significantly decrease with this decrease in K and *VAF*_{reflex} correspondingly increased, as demonstrated in Fig. 4.9. As expected, the *VAFs* at times before K_s and after B_e, i.e. during stationary conditions, remained relatively constant in both simulations.



Figure 4.9: *VAFs* between total torque and predicted torques, when using a larger change in the elastic parameter (K).

Fig. 4.10 displays the true (solid line) and predicted (dashed line) total torque (A), intrinsic torque (B) and reflex torque (C), for a single realization. The estimated torques from each model followed very closely the simulated (true) signals. As shown in the Fig. 4.11A, there was little variation between the true and predicted total torque when examining different realizations across time. This demonstrates the repeatability of the time-varying behaviour generated from this simulation. The total torque was well predicted at different points in time across the ensemble (Fig.4.11B). The *VAF*_{total}, which

represent the amount of predicted torque attributed to the total stiffness model, were consistent across time and between realizations.



Figure 4.10: True (solid) and predicted (dashed) torque records for a single realization. The dashed lines indicate the times of parameter changes.



Figure 4.11: True and predicted total torque for 3 different trials (A), with the corresponding $VAF_{TQ}(N)$ for each trial. True and predicted total torque at 3 different times (B), with the corresponding VAF_{total} . The dotted lines indicate the times of parameter changes.

4.3.1.3 Parametric Models

Parametric models were fit to the non-parametric IRFs to evaluate how closely they matched the actual models. These best "least-squares" fits were found using a Levenberg-Marquardt nonlinear least-square fit algorithm to minimize the mean squarederror between the parametric and non-parametric IRFs [3, 57]. Reflex stiffness parameters were determined using an exhaustive search where the estimation was repeated for delays between 30 and 80 ms at 10 ms intervals. The reflex stiffness 'best-fit' was that which yields the lowest overall error for the parameter set and delay.

The least-squares method used to calculate the parametric fits requires good initial estimates of the parameters, therefore they were first chosen as the simulated values at the initial time. For subsequent fits, the initial parameters were taken as the previously estimated parameters. This was done to get the best fit during the ramp changes, as the estimated parameters at the previous time point should be close to the next parameter value. To account for poor curve fits, the algorithm verified that the VAF_{fit} (the percentage variance accounted for between the non-parametric and parameters as the initial estimates at the next time point. If VAF_{fit} was less, then it would search until one was found that satisfied the VAF_{fit} criterion. For these non-parametric curves, the VAF_{fit} criterion was chosen as 95% for both the Hammerstein and intrinsic compliance.

The parametric fits were evaluated using $VAF_{fit}(t)$, and were found to be very high across time. This is shown in Fig. 4.12 with the $VAF_{fit}(t)$ for intrinsic (A) and reflex (B) simulated (solid lines) and estimated (dashed lines) models against time. The simulated $VAF_{fit}(t)$ were 100%, as they were generated based on the parametric models. This demonstrates that the least-squares fitting paradigm was able to accurately estimate the parameters of the simulated system. The parametric models were good fits to the IRF estimates particularly for the intrinsic compliance (mean 99%). For the estimated Hammerstein system, the VAF_{fit} was consistently high across time (mean 98%).

The original (non-normalized) reflex stiffness models were used for the 2^{nd} order parametric model fitting. Because the two systems (simulated and estimated) were not normalized, comparisons cannot be made since the gain distribution of the Hammerstein systems is unknown. To compare the two systems, the overall gain (*G*) of the reflex stiffness block had to be used. This was calculated as the product of the gain of the linear model (*G_R*) and the gain of the non-linear element. The reflex gain, *G_R*, was found from the parametric fit. The gain of the non-linear element was found as the slope of the linear portion of the polynomial.



Figure 4.12: Parametric fit % VAF to the simulated (solid line) and estimated (dashed line) systems: intrinsic compliance (A) and reflex stiffness (B). Parameters of intrinsic compliance (C, E, G) and reflex stiffness (D, F, H) from parametric fit to simulated (solid line) and estimated (dashed line) systems.

Since the VAF_{fit} was high across time for both models, all parameters across time were examined. The simulated and estimated parameters resulting from the parametric fits are shown across time in Fig. 4.12, for intrinsic compliance (C,E,G) and reflex stiffness (D,F,H). Although the estimated parameters fluctuate around the desired values, the time-varying trends in *B*, *K* and *G* are clearly estimated. The values of *I*, ω and ζ (*z*) are estimated clearly as having stationary behaviour. Recall that the least-squares method was applied to the simulated systems and the resulting parameters and VAF_{fit} are indicated in Fig. 4.12 as the solid lines. Given the simulated systems, the least-squares fitting paradigm was capable of correctly estimating the parameters. Therefore any deviation of the parametric fits to the estimated IRFs is likely not due to the fitting paradigm itself but to the identification algorithm.

4.3.1.4 True and Estimated Systems

The true and estimated systems are presented at specific points in time in Fig. 4.13 and Fig. 4.14. The IRFs were taken from the following points in time (relative to the simulated parameter changes): at 0.5 s, 200 ms before any ramp start (bottom plots); at 0.85 s, half-way through the ramp change in K; at 1.15 s, half-way through the ramp change in G; at 1.45 s, half-way through the ramp change in B; at 1.8 s, 200 ms after the end of all ramp changes (top plots). Fig. 4.13B and Fig. 4.14B plots the estimated IRFs (lines with markers) for the intrinsic compliance and reflex stiffness, respectively, with their 2nd order parametric fits (lighter lines with no markers), as well as the simulated IRFs (dark, dashed lines). In Fig. 4.13A and Fig. 4.14A, the intrinsic stiffness and the SNL are plotted for both the estimated and simulated systems.

The time-varying nature in intrinsic stiffness is not very apparent (Fig. 4.13A). However, when we look at intrinsic compliance (Fig. 4.13B), the curves increase in size as time increases (bottom to top). The overall stiffness of the ankle is thus decreasing (increase in compliance) as the plantarflexing ramp occurs. The simulated curves and estimated parametric fits were very similar for intrinsic compliance, again demonstrating the good fit to the data.

Fig. 4.14 show the elements of the normalized, smoothed Hammerstein system: the static non-linearity (A) and the linear system (B). As the system was normalized to have a DC gain of unity for the linear element, the time-varying nature of the system is only apparent in the SNL. The polynomial range decreased over time (bottom to top), which represents a decrease in the reflex stiffness, as simulated. For the linear system, the simulated curves and estimated parametric fits were very similar, demonstrating the good fit to the data.

Because the block-structure Hammerstein model is highly non-linear, higher order polynomials must be used to represent the SNL. The higher order polynomials tend to be less accurate at the edges of the data set because they often include oscillations [58]. This was evident in the results as the polynomials were not as well estimated at the extremes of the input amplitude, as shown by comparing the simulated and estimated SNLs at time 0.5s (Fig. 4.14A). The other plots may not show this discrepancy as significantly because of the chosen input amplitude to the polynomials.



Figure 4.13: Estimated IRFs (markers with dark line), their parametric fits (lighter line) and simulated IRFs (dashed lines) for intrinsic compliance (B) and intrinsic stiffness (A) IRFs, at various times indicated in A (time increases from bottom to top).



Figure 4.14: Estimated IRFs (markers with dark line), their parametric fits (lighter line) and simulated IRFs (dashed lines) for reflex stiffness IRFs (B) and the static non-linearities (A), at various times indicated in A (time increases from bottom to top).

To quantitatively evaluate the quality of the identification, comparisons were made between the true and estimated systems, along with the true and predicted output signals. The $VAF_{IRF}(t)$ was computed across the ensemble at time t between the true and estimated IRFs. For the reflex linear dynamics, $VAF_{IRF}(t)$ was utilized between the normalized systems. The $VAF_{snl}(t)$ was computed between the normalized true and estimated polynomials over the range of input values used to estimate the system at each instant. Similarly the $VAF_{TQx}(t)$ between the simulated torques and predicted torques, was computed based on the reflex stiffness, intrinsic stiffness or both (i.e. 'X' is 'r', 'i' or 'n').

Fig. 4.15 illustrates the plots of VAF_{IRF} (A, B, E), VAF_{snl} (F), VAF_{TQr} (D) and VAF_{TQi} (C) from the final iteration. As can be seen in Fig. 4.15, the estimated intrinsic IRFs and torques matched very well with the true behaviour (left plots), as did the reflex

pathway (right plots). The final iteration showed that the intrinsic stiffness model was estimated within 99.7%, the reflex linear pathway within 97.8% and the reflex static nonlinearity within 99.1% of the true models. Also demonstrated was that the estimated system predicted the torque signals accurately, with a mean intrinsic torque VAF_{TQi} of 98.1%, reflex torque VAF_{TQr} of 96.0% and net torque VAF_{TQn} of 98.9%. These are very high VAF between the true and estimated systems and torques, demonstrating the ability of the time-varying algorithm to capture the changing dynamics with this given input.



Figure 4.15: *VAFs* between true and estimated intrinsic (A,C,E) and reflex (B,D,F) systems and torques versus time. VAF_{IRF} , (A,B,E); VAF_{TQx} (C,D); VAF_{snl} (F).

4.3.2 Experimental PRBS Input

The simulation results presented in this section used experimental PRBS position input records. The input was a PRBS sequence of 0.03 rad in amplitude with an 80 ms switching interval. The experimental protocol is outlined in Chapter 5.

4.3.2.1 Simulated Signals

Fig. 4.16 shows input-output realizations using the experimental inputs with the simulated time-varying systems. Notice the reflex torque records have the expected 'twitch-like' response with a delay of 40 ms resulting from the pulse-like dorsiflexion position changes. The reflex and intrinsic torques shown in Fig. 4.16 contribute about the same amount (approximately 5 Nm) to the total torque. Thus the experimental PRBS input was capable of generating a larger reflex response from the simulated system than the Gaussian input, as found previously [3].



Figure 4.16: Simulated position and corresponding torque signals from multiple realizations (the signals are offset vertically for clarity), using actual experimental PRBS position records as input to the simulation.

4.3.2.2 Model Evaluation

Fig. 4.17 shows the *VAFs* of the torques attributed to each stiffness model, $VAF_{total}(t)$, $VAF_{intrinsic}(t)$ and $VAF_{reflex}(t)$, with the parameter changes indicated by the dashed lines. VAF_{total} is high throughout the simulated time-varying behaviour, with a mean value of 95.8%. The *VAF_{intrinsic}* has an average of 56.5%, and decreases with the decrease in the elastic parameter K, much more compared with the Gaussian input. VAF_{reflex} averages at about 48.8% and decreases significantly with the decrease in reflex gain G_R. The reflex torque accounted for much more of the total torque with the PRBS compared with the Gaussian input (mean 19.6%). The shape of the change in these *VAFs* across time is similar to when using the Gaussian input, however the PRBS input excites the reflex pathway more and was more significantly affected by a decrease in the elastic parameter. The effect of changing the viscous parameter B had nearly the same effect, a slight decrease in *VAF_{intrinsic}* and corresponding increase in *VAF_{reflex}*.



Figure 4.17: VAFs between total torque and predicted torques, using the experimental position with the time-varying system. The dashed lines indicate where the simulated parameters changes start and stop.

The plot of VAF_{total} shows some significant drops, which correspondingly appear in VAF_{reflex} and $VAF_{intrinsic}$. These low points may be where the ensemble input did not provide a rich enough signal to permit a good identification. Fig. 4.18 shows the probability density functions of the Gaussian (A,B) and PRBS (C,D) position and velocity inputs across the ensemble at two specific times. The Gaussian inputs have a wider distribution than the PRBS inputs, for both position and velocity. The PRBS velocity distribution show that it is mostly at zero. The Gaussian probability density function does not vary substantially from one time to another, whereas the PRBS probability density function shows quite a difference. Given the different properties of Gaussian and PRBS inputs across the ensemble, this could explain why the model described the data consistently across time with the Gaussian input than with this PRBS input. This theory will be discussed further in the discussion of Chapters 4 and 5.

The points where the model did not describe the data as well, such as around 1.0 s, will not be considered as part of the data set. Any subsequent results, for this data set, will not include points where the VAF_{total} was lower than 92%. This value was chosen by trial and error, to retain enough data points to get a picture of the system estimates across time, but also obtain a steady VAF_{total} across time.



Figure 4.18: Probability Density of the input velocity estimated across time (A,C) and across the ensemble (B,D) for Gaussian input (A,B) and PRBS input (C,D).

Fig. 4.19 displays the true (solid line) and predicted (dashed line) total torque (A), intrinsic torque (B) and reflex torque (C), for a single realization. There are points in time

where the predicted torques do not match the simulated values, and these correspond to where the VAF_{total} was low.

Fig. 4.20 show total torques for different realizations (A) and at different points in time (B). The true and predicted total torques showed very little deviation between realizations or at different points in time.

The intrinsic torque and reflex torques are in fact in the same range, roughly -4 to 2 Nm for this particular trial in Fig. 4.19. This is quite different from the Gaussian input, where the intrinsic torque accounted for the majority of the torque. The PRBS input has a much lower mean absolute velocity and power at lower frequencies than the Gaussian inputs. This velocity distribution elicits more reflex activity.



Figure 4.19: True (solid) and predicted (dashed) torque records for a single realization. The dashed lines indicate the times of parameter changes.



Figure 4.20: True and predicted total torque for 3 different trials (A), with the corresponding $VAF_{TQ}(N)$ for each trial. True and predicted total torque at 3 different times (B), with the corresponding VAF_{total} . The dotted lines indicate the times of parameter changes.

4.3.2.3 Parametric Models

To determine how well the estimated IRFs were modelled by the parametric fits, the *VAF* of the fits were calculated at each point in time and plotted in Fig. 4.21. Parametric models where the VAF_{fit} was less than 90% were not considered good fits, and therefore the parameters at these points were not examined. Therefore in Fig. 4.21 there are some breaks in the dashed lines, as this is where the fits were not good. Intrinsic compliance from the good fits had a mean of 97.2% and the reflex pathway from the good fits has a mean of 95.9%. The poor fits for compliance dropped to a VAF_{fit} as low as 40% and for reflex stiffness as low as 5%. Similar to the Gaussian input, the IRF fits for the reflex pathway were not as good as the intrinsic pathway.

Recall that the simulated values were chosen as the initial guesses for the leastsquares estimation of the parametric fits. The VAF_{fit} criterion was chosen as 85% for both the estimated Hammerstein system and intrinsic compliance model. This was chosen lower than in the case of the Gaussian input (95%) because the estimated systems were not as well modelled.

The simulated and estimated parametric fit values are shown across time in Fig. 4.21, for the intrinsic compliance (C,E,G) and reflex stiffness (D,F,H). There are definitely more oscillations around the desired values as compared with the Gaussian input. Although there is more variation in parameter estimates across time, the time-varying behaviour is still evident in *B*, *K* and *G*. The points where the parameters were not shown because of a low VAF_{fit} corresponded to the points in time where the model did not describe the data as well (VAF_{total}).

Although the least-squares fitting algorithm was accurate for the simulated systems, this is partially dependent on the choice of initial parameters. When fitting to the estimated systems, the target VAF_{fit} was used to ensure initial parameters were chosen based on previous good fits. However, the parameters were changing significantly during the ramp. If the VAF_{fit} of the previous few systems were low, then the initial parameters were less accurate. While we could have used the actual simulated values as the initial parameters, this process is a realistic algorithm to use for experimental data. The issues with estimating the parametric models with the experimental data are further evaluated in the discussion of Chapter 5.



Figure 4.21: Parametric fit % VAF to the simulated (solid line) and estimated (dashed line) systems: intrinsic compliance (A) and reflex stiffness (B). Parameters of intrinsic compliance (C, E, G) and reflex stiffness (D, F, H) from parametric fit to simulated (solid line) and estimated (dashed line) systems.

4.3.2.4 True and Estimated Systems

The estimated (lines with markers) and simulated (dark, dashed lines) intrinsic compliance (B) and intrinsic stiffness (A) IRFs are plotted in Fig. 4.22, along with the 2nd order parametric fits to compliance (lighter line with no markers). Similarly the estimated and simulated reflex stiffness (B) and SNL (A) are plotted in Fig. 4.23. Each row corresponds to a particular time and time increases from bottom to top.

The system's intrinsic time-varying behaviour is quite apparent, with intrinsic compliance increasing over time (thus decrease in stiffness). The SNL displayed an overall decrease across time; however it displayed some unusual switching of the polynomial direction from 0.85 to 1.15 s. This was not seen when using the Gaussian

input. The estimated SNL did not match the simulated one, except at 0.5 s. Also the estimated reflex stiffness at times up until 1.15 s, were quite different from the simulated systems. Clearly the algorithm was not as accurate in estimating the system dynamics using this experimental input as compared to the Gaussian input.



Figure 4.22: Estimated IRFs (markers with dark line), their parametric fits (lighter line) and simulated IRFs (dashed lines) for intrinsic compliance (B) and intrinsic stiffness (A) IRFs, at various times indicated in A (time increases from bottom to top).



Figure 4.23: Estimated IRFs (markers with dark line), their parametric fits (lighter line) and simulated IRFs (dashed lines) for reflex stiffness IRFs (B) and the static non-linearities (A), at various times indicated in A (time increases from bottom to top).

Comparisons were made between the true and estimated systems, along with the true and predicted output signals. These results are shown in Fig. 4.24, but only the points are showing where the VAF_{IRF} for the respective system was greater than 90%.

The intrinsic stiffness pathway (upper two left plots) was well modeled throughout most of the behaviour until the last 400 ms. The intrinsic compliance was actually better modeled near the end of the behaviour. However, the lack of fits above 90% when compared with the Gaussian input, demonstrated that the systems were not estimated as well with the experimental input.

The reflex stiffness pathway (right plots) appeared to be well modeled throughout most of the behaviour when comparing the linear elements and the static non-linearities between the true and estimated systems. However, the estimated reflex torques were clearly not as well matched with the true torques, shown by the significant drops in VAF_{TQr} . This was also evident in Fig. 4.19 where the actual reflex torques were plotted against one another. Overall, these Hammerstein systems were not well estimated.



Figure 4.24: *VAFs* between true and estimated systems and torques versus time (Intrinsic on left, Reflex on right; Upper plots VAF_{IRF} , Middle plots VAF_{TQx} ; Lower left plot VAF_{IRF} Compliance; Lower right plot VAF_{snl}).

4.3.3 PRBS Inputs

The simulation was attempted with computer-generated pseudo-random binary sequence (PRBS) inputs of varying switching rates (including 80 ms); however the identification did not work at all, with the exception of an extremely fast switching rate of 10 ms. Even when the PRBS inputs were filtered the identification would not work. Unfortunately the preferred input type for experiments has been found to be PRBS inputs, as they elicit strong reflexes with a low mean absolute velocity, whereas Gaussian inputs have been found to inhibit reflex activity [3].

4.4 Discussion and Conclusions

This chapter presents a new technique for the identification of time-varying joint dynamics. A time-varying simulation of the ankle joint was used to generate time-varying ensemble data to test the algorithm. Gaussian inputs were used to validate the algorithm's abilities. The model was capable of describing the data extremely well, and separating the two stiffness components accurately. The estimated systems and torques matched the simulated very well.

The simulation was repeated using experimentally obtained PRBS inputs. The PRBS inputs generated larger reflex activity as compared with the Gaussian input, when applied to the same time-varying simulated systems. The PRBS inputs produced estimates that described the data well at most points. However poor descriptions did result at certain points in time. Similarly models at these times were not well described by the parametric 2nd order fits. A discussion will follow on why certain models were not well estimated. Overall, the estimated systems did not match the simulated systems well. When trying the simulation using computer-generated PRBS inputs, the algorithm did not work at all.

The main question that results from these simulations is why does the algorithm perform so well with Gaussian inputs and not with PRBS inputs? This is likely due to the non-ideal properties of the experimental PRBS input. One possibility is that there may not be any or few perturbation changes at specific times across the ensemble, which is how the IRFs are estimated. The position only changes between two values, which results in a binomial input distribution. Similarly the velocity has a limited trimodal distribution where it spends most of the time at zero, as compared with inputs like Gaussian. Further discussion of the algorithm's ability to estimate system dynamics using PRBS inputs will be presented in Chapter 5.

Compared with the computer-generated PRBS inputs, the experimental PRBS inputs were at least able to demonstrate the algorithm's ability to identify dynamics at some times. This is likely because it is filtered by the effects of the actuator and the subject. The computer-generated PRBS inputs, even when low-pass filtered, are not representative of actual experimental data.

Improvements should be investigated for the algorithm, not only related to the PRBS inputs. One item to consider is the representation of the static non-linearity. For all estimated Hammerstein systems, the polynomials were not well estimated at the edges of the data set (i.e. input velocity extremes). Future consideration for the Hammerstein system would be to use cubic splines, instead of polynomials, to represent the static nonlinearity. Dempsey and Westwick tested cubic splines representing the SNL component of a Hammerstein system, using experimental data from the ankle between velocity and gastrocnemius-soleus EMG [58], instead of reflex torque as in this thesis. They found much better estimates at corners and edges of the SNL using cubic splines than using polynomials. It would be useful to investigate whether this substitution might improve the estimates of the SNL under time-varying conditions and contribute to a higher accuracy for identification of Hammerstein systems.

The parallel-cascade identification technique for time-varying systems has proven to estimate the simulated system's dynamics well, given Gaussian inputs. The PRBS inputs gave an indication of the expected results, although not as well estimated at each time, particularly in the Hammerstein estimations. Given a subset of data with certain points in time omitted due to the poor estimates, the mean total variance accounted for by the model was 96% for the PRBS input and 99% for the Gaussian input. The use of the experimental PRBS input was very important since the computer-generated PRBS inputs were not able to function with the identification. To maximize the benefits of the simulation, the algorithm should be capable of working with computer-generated PRBS inputs. The expected results could be easily generated, prior to acquiring all 400 realizations from a subject. In the future, this issue should be further investigated in terms of attempting to mimic more closely the measured ankle position from PRBS inputs.

Thus two objectives of this thesis have been met; the development of a timevarying, parallel-cascade identification algorithm and its validation with simulated data. The next objective for this thesis was to acquire experimental time-varying data and apply it to the time-varying, parallel-cascade identification algorithm, as presented in Chapter 5.

5. Experiments

The simulation study in Chapter 4 demonstrated the identification technique's ability to estimate the system dynamics. The next step was to test the technique with real data. The experimental protocol, which involved imposing a ramp to the ankle with superimposed perturbations, and data analysis are outlined in this chapter. Pilot experiments were performed on one subject to investigate a variety of input perturbations which would best suit the needs of the identification algorithm. Using the input perturbation, experiments were carried out on three subjects. The results are presented and the ability of the identification algorithm is evaluated from this preliminary data set.

5.1 Experimental Protocol

The experimental protocol was based on that by Kirsch and Kearney [41, 59]. An imposed stretch was applied to the ankle. Perturbations were superimposed on this ramp stretch to enable identification of the joint dynamic stiffness. Over 300 realizations of this same behaviour were obtained for use with the ensemble-based time-varying, parallel-cascade identification algorithm. Although the movement was not voluntary, the simple time-varying pilot data was useful for testing the algorithm.

5.1.1 Subjects

Three subjects, ranging in age from 23 to 28, two males and one female were examined. Subjects had no history of neurological disorders. Each subject had a custom-fit boot fabricated prior to experimentation, as described in Section 3.2. The Ethics Certificate applicable to our experimental studies is included in Appendix D.

The subject's ankle was placed in their zero position, defined as a 90 degree angle between the foot and tibia. All other positions were taken relative to this defined zero position.

5.1.2 Initial Trials

Pulse trials were used to determine the position, called the optimal operating position (OOP), where the subject had the largest reflex torque [50]. The trials began at a position of large plantarflexion near to their range of motion limit. A short pulse, of width

40 ms, was applied to the foot, once the subject had matched the required target torque of -5 Nm to within $\pm 10\%$. The visual feedback displayed the error between the low-pass filtered torque and the torque target signal and the subjects were asked to minimize it. Five to ten pulses were recorded at each position and their responses averaged.

Reflex torque was calculated by finding the minimum of the twitch-like reflex response. This minimum value, shown in Fig. 5.1B and Fig. 5.1D by the cross formed by dotted lines, was measured relative to the baseline torque before the pulse was applied. The absolute values of the reflex torques are indicated for pulse trials at two different positions. Notice that the torque exhibits the twitch-like response after the pulse is finished. The pulse width was shorter than the reflex delay and therefore the intrinsic and reflex mechanisms of stiffness could be separated simply on the basis of delay.



Figure 5.1: Averaged pulse trials from Subject C at two ankle positions; Position (AC) and Torque (BD) at -0.135 rad (AB) and at 0.065 rad, the OOP (CD). The cross formed by the dotted lines marks the maximum reflex torque. The actual reflex torque value is taken relative to the baseline torque.

The foot was then dorsiflexed in small increments and the procedure repeated until the reflex torque reached a plateau or the patient was uncomfortable. The OOP was found to be at 0.065 rad for Subject C (Fig. 5.1). The OOPs for all subjects were found to be in positions of dorsiflexion.

The selection of the OOP assured there would be strong reflexes at the end position. The subject's range of motion (ROM) was recorded and used to determine the maximum ramp amplitude that could be applied. The ramp amplitude was similar for all subjects. Table 5.1 shows the start position, end position, ramp amplitude, ROM and ramp amplitude as a percentage of ROM, for all subjects. Note that the ramp amplitudes are very similar, ranging from 0.2 to 0.225 rad.

Subject	Ramp start position [rad]	Ramp end position [rad]	Ramp Amplitude [rad]	Range of Motion (ROM)	Ramp amplitude/ ROM (%)
Α	-0.1	0.1	0.2	0.620	32.3
В	-0.175	0.05	0.225	0.542	41.5
С	-0.1	0.1	0.2	0.534	37.5

Table 5.1: Ramp and Range of Motion parameters

5.1.3 Control Trials

Two types of control trials were performed prior to the imposed ramp and perturbation trials:

 Control Perturbation Trials: Stationary trials executed at various locations throughout the ramp movement using only the perturbation.

The control perturbation trials were performed to allow comparisons between the static and time-varying case at corresponding positions throughout the ramp movement. Trials of 30 s in length were performed at 11 positions equally spaced through the ramp movement, while the subject maintained the target torque of -5 Nm. The visual feedback was the same as for the pulse trials.

The data were then given to the time-invariant, parallel-cascade identification technique to determine the contributions from the reflexes. We were then able to compare the IRFs determined from the ramp and perturbation trials (Section 5.1.4) at a particular ankle position with the control perturbation trial at that same location. Previous work has

found that behaviour during stationary conditions differs from that during time-varying conditions [19, 29], and thus we hoped to affirm this conclusion.

2) Control Ramp Trials: Multiple trials using only the imposed ramp.

The control ramp trials were performed for two sets of 30 realizations each, following the procedure described in the next section. The difference was that no PRBS perturbations were superimposed on the ramp. The ramp stretch imposed alone, permits the effect of the stochastic perturbation to be examined. We can examine the ensemble response in GS EMG to the trials with only the ramp and to the ramp and perturbations as well as the ensemble torque response, to see if there was a significant effect of the stochastic perturbations on ramp responses.

5.1.4 Imposed Ramp Trials

Rapid imposed ramp trials were performed with the visual display and target torque limits set as for the pulse trials. The starting position of the ramp was the optimal operating position (OOP) minus the ramp amplitude (see Table 5.1) so that the imposed movement would end at the OOP. Pseudo-random binary sequence (PRBS) perturbations were applied while the subject generated a plantarflexing torque. Once the subject matched the target torque within $\pm 10\%$, the ramp movement was initiated in the dorsiflexion direction. Typical trials are shown in Section 5.3.2.

The PRBS input has an amplitude of 0.03 rad and a switching interval of 80 ms. This perturbation was selected to elicit reflex activity because of its low mean average velocity. It also has a fast switching rate to provide position changes during the ramp, so that the time-varying system estimates can be estimated throughout the ramp.

The ramp input was filtered with a 1st order low pass Butterworth filter with a cutoff of 50Hz to remove sharp corners. The peak velocity was 0.6 rad/s, consistent for all subjects. Data was recorded for at least 800 ms prior to the ramp onset, for all subjects. The ramp duration ranged from 340-390 ms, depending on the ramp amplitude chosen for the subject. The duration after the ramp, before the foot was returned to the initial position, was at least 600 ms. Perturbations were applied continuously, with the sequence repeating itself every 16 s. The duration recorded for each trial was 3 s. The foot was returned to the initial position and after about 1 second (to allow for transients to die down) another ramp could be applied. However the subject had to again match the correct torque level before the ramp stimulus was triggered. Approximately 30-40 trials were acquired sequentially followed by a roughly 2 minute rest period (no perturbations) and 10-15 sets were recorded in total. After approximately half the required sets had been completed, the subject walked around during a 10 minute break.

Because the subject had to match the desired torque before the ramp was initiated, the ramp started at random times throughout the PRBS sequence. This is a crucial requirement for the identification algorithm, as the algorithm assumes that each realization consists of different random zero-mean inputs. The subject received no warning that a ramp was going to start, and was instructed 'not to react' voluntarily to the ramp. This is a challenging task, but with the number of trials performed, the majority of the responses were very similar as found in the previous study [41]. This meets another major assumption for the identification algorithm, that the system must undergo the same time-varying behaviour for each realization. A trial selection process was used to select the most similar trials based on torque standard deviation as described in Section 5.2.1.

5.2 Analysis

A crucial assumption underlying time-varying ensemble methods is that the system undergoes the same time-varying behaviour for each realization. Two post-processing steps were taken to ensure this requirement was met. Firstly the trials were aligned according to a common feature of the time-varying behaviour. Secondly trials that showed the largest variability of torque compared with other trials were rejected.

5.2.1 Trial Alignment

Sampling was initiated for each trial once the subject had matched the desired torque. Ideally the ramp should have been initiated at exactly the same time for each trial. However due to timing discrepancies between the data acquisition hardware and the Simulink model that controlled the ramp changes, there were slight misalignments between trials (i.e. milliseconds). This variability would bias the results of the ensemble time-varying algorithm and as such were resolved with the following analysis.

Trials were aligned based on the ramp input signal, sampled without the PRBS perturbation. All trials were aligned to the trial where the ramp occurred earliest and then truncated to 1000 samples (1 second) after the start of the ramp. The ramp duration ranged from 340-390 ms, thus a minimum of 600 ms of data was kept after the ramp.

Fig. 5.2 demonstrates the alignment procedure for 4 realizations. The trials shown in Fig. 5.2A have slightly staggered input ramp start times. After the alignment to the earliest occurring ramp input, these trials (Fig. 5B) all started at the same point. All channels of data (position, torque, input ramp, GS EMG, TA EMG) were shifted accordingly for each realization. This is demonstrated in the plots of position before (5C) and after alignment (5D).



Figure 5.2: Input ramp (AB) and position (CD) before (AC) and after (BD) alignment for 4 realizations; Subject A.

5.2.2 Trial Selection

The subject matched the torque feedback to initiate the ramp and was told 'not to react' to the ramp. If the subject performed consistently, each trial should exhibit similar time-varying behaviour. However, given the large number trials, the subject will likely alter their torque after sampling was initiated and 'react' to the ramp, for some of the trials. Trials with different behaviour from the majority will skew the results from the ensemble time-varying algorithm.

Thus, a trial selection procedure was required to remove trials which were the least similar based upon the output torque. This process calculated the ensemble standard deviation of the torque across time from each aligned trial with the ensemble mean removed. These values were sorted in ascending order and plotted against the realizations, as shown in Fig. 5.3.

A threshold level was then selected, and only the trials with a torque standard deviation below that level were kept. For subject A, a torque cut-off of 2.5 Nm was selected (see dashed line Fig. 5.3) which preserved 467 out of 500 aligned trials. Selecting a more stringent cut-off torque standard deviation, would yield trials that were more similar. However, the identification technique would be less accurate as the number of trials decreases, since the number of parameters used to generate the models (IRFs) depends on having many more trials than the IRF length. This is the inherent trade-off that must be considered when using ensemble methods.



Figure 5.3: Sorted torque standard deviations with dashed line indicating the threshold chosen; Subject A

5.3 Results

The results from the three subjects based on the experimental protocol of Section 5.1 will be presented in Sections 5.3.1-5.3.5.

5.3.1 General Behaviour

The data obtained from the experiments consisted of the position, torque, input ramp, GS EMG and TA EMG. Prior to identification, the trials were aligned and selected, as described in Section 5.2, and the ensemble mean was removed. The position was differentiated to give velocity. A sampling rate of 1 kHz was used to capture the reflex delay. The data were then decimated to 100 Hz, since only the low frequencies are of interest and enough frequency content will be retained to fully characterize ankle joint dynamics.

Table 5.2 shows, for each subject, the total time of each trial, the number of trials, and the number of trials remaining after choosing the torque threshold. The selected torque threshold levels varied between subjects because of each subject's ability to match the desired torque.

Subject	Duration of each trial (s)	Total no. of trials	No. of trials selected	Torque threshold (Nm)
Α	1.72	500	440	2.3
В	1.72	332	307	3.5
С	1.73	500	421	3.2

Table 5.2: Trial Alignment and Selection Results

Fig. 5.4 shows typical trials from Subject A, with position (A) and torque (B) for multiple aligned and selected trials. Fig. 5.4C and 5.4D show the same trials with the ensemble mean removed. In the position records with the ensemble mean removed, only the input perturbation remains.



Figure 5.4: Multiple Trials with (CD) and without (AB) ensemble mean removed for position (AC) and torque (BD); Subject A. Signals are offset for clarity.

5.3.2 Ensemble Behaviour

The ensemble behaviour for each subject is shown in Figs. 5.5-5.7. The position, torque, GS EMG and TA EMG were ensemble averaged and are shown as the solid dark lines. The ensemble standard deviations were also compared and are shown as the dotted light lines. The GS and TA EMG were rectified and by convention the GS EMG is shown increasing in the negative direction and the TA EMG increases positively. Negative position and torque indicates plantarflexion.



Figure 5.5: Ensemble means (solid, dark lines) and standard deviations (light, dotted lines) of position (A), torque (B), GS EMG (C) and TA EMG (D), from the aligned and selected trials; Subject A.



Figure 5.6: Ensemble means (solid, dark lines) and standard deviations (light, dotted lines) of position (A), torque (B), GS EMG (C) and TA EMG (D), from the aligned and selected trials; Subject B.



Figure 5.7: Ensemble means (solid, dark lines) and standard deviations (light, dotted lines) of position (A), torque (B), GS EMG (C) and TA EMG (D), from the aligned and selected trials; Subject C.

For all subjects, the ensemble position standard deviation (A, dotted line) remained constant in time, demonstrating that the stochastic perturbation was stationary despite the superimposed ramp and corresponding large changes in torque. The standard deviation was also computed for single trials across time (after subtracting the ensemble mean), and found to be very close to the position ensemble standard deviation. This indicates that the perturbation was unchanged across trials and that its timing with respect to the ramp onset was largely random across trials.
The ensemble torque records (B, dark lines) show the resistance of the ankle joint to the imposed stretch, with the torque level more than doubling in amplitude for all subjects. All subjects had similar ensemble torque responses. During the ramp, the torque level increased (negatively) at a fairly steady rate, then immediately after the ramp end, the torque level decreased in a smooth fashion to a steady torque level.

The GS EMG ensemble data show a small increase after the ramp, approximately 3 μV for Subject C, which is not a very strong response. The other subjects showed even less of a change in the GS EMG. The ramp slope was much slower (by a factor of 10) than previously used [41], therefore the GS did not display a huge burst of activity when the ramp was imposed. The TA EMG ensemble data also displayed a small increase after the ramp, timed with the activity in GS. It is likely that during the imposed ramp, a small amount of co-contraction occurred.

Kirsch and Kearney compared the ensemble GS EMG from the two trials and demonstrated that there was little effect on the stretch reflex properties from the stochastic perturbation [41]. They found similar form and latency for the EMG within a subject and by taking the average of all subjects. We compared the ensemble GS activity from the perturbed ramp trials with the unperturbed ramp trials and found them both to be very small for all subjects.

We also compared the ensemble average torque between the perturbed and unperturbed ramp trials. This is shown in Fig. 5.8 with the dark lines corresponding to the ensemble torque from the ramp plus perturbation and the lighter, dashed lines indicating ensemble torque from ramp only. The thin lines correspond to the standard deviations of the respective ensemble torques. In all subjects, pre-ramp torque was consistent between the ramp alone and the ramp plus perturbations and also until 200 ms after the imposed ramp. With perturbations, the ensemble torque response was larger than with only the ramp, for all subjects.



Figure 5.8: Effect of stochastic perturbation on ramp responses; Subjects A, B, and C; Ensemble torque record (thick lines) and the torque standard deviation (thin lines) from ramp trials with perturbations (solid lines) and without perturbations (dashed lines).

The behaviour of the ensemble torque for Subject B was slightly different between the ramp only and ramp plus perturbation trials. The raw data was examined for the ramp only trials and this plateau behaviour was consistent throughout most of the trials. The subjects were told 'not to react' to the imposed ramp, however this likely took some practice. The control ramp trials were performed before the regular trials, therefore Subject B may have been reacting to the ramp initially.

There was little difference in the shape of the ensemble torque records between the perturbation and no perturbation case, for subjects A and C. These results are similar to those found previously using the faster ramp and a larger initial contraction level [59]. Given the small differences in the shape and timing of the ensemble torques after the imposed ramp, we can assume that the overall behaviour was not distorted by the perturbation.

5.3.3 Position Records

The position, with the ensemble mean removed, is illustrated for 5 realizations in Fig. 5.9 for each subject, where the dashed lines indicate the respective ramp start and stop. Although the ensemble mean was removed from all the position trials, the trials show a slight increase in position amplitude that roughly corresponds to the ramp timing. The ensemble position record, as shown in Section 5.3.2, only included the ramp. Thus these residual position effects may be due to the actuator behaviour during the ramp. The behaviour of the actuator during this ramp movement with superimposed perturbations has not been fully investigated. The ideal position records would show the PRBS input as a stationary signal, with no effects from the imposed ramp.



Figure 5.9: Position records with ensemble mean removed from 5 realizations; for all subjects. The dashed lines correspond to the ramp start and stop.

To fully understand the results from the simulation and experiments, it was important to determine what effect, if any, these position deviations would have on the identification procedure. Therefore a stationary system was simulated by maintaining the same stiffness parameters across time. First, the Gaussian input from Section 4.3.1 was applied to the stationary system. The system estimates described the data very well, which demonstrated the ensemble identification algorithm's capability of correctly estimating a stationary system. Secondly, the experimental PRBS input was applied to the time-invariant system. The simulation results of the stationary and time-varying systems using the experimental PRBS input will now be presented.

The VAF of the torques attributed to the total (A), intrinsic (C) and reflex (E) stiffness models, are shown in Fig. 5.10 for both systems, along with the torque variances (B,D,F). The VAFs and torque variances are indicated as the dashed curves for the time-varying simulation and as solid curves for the stationary simulation. The dashed lines indicate the parameter changes occurring in the time-varying simulated system. The thick, short lines indicate the experimentally imposed ramp start and stop times, which are correlated with changes in the PRBS position as shown in Fig. 5.9.

The VAFs performed similarly at stationary times: prior to the first dashed line (K) and after the last dashed line (B). Any deviation occurred between the times of parameters variations. There did not seem to be a large difference between the two systems when the ramp was initially applied.

Differences between the stationary and non-stationary system estimates were more evident in the torque variances. The intrinsic torque variances of the two systems deviate at the first dashed line (K), whereas the reflex torque variances do not change at all. The reflex torque variances of the two systems deviate when the second dashed line (G) is reached.

Hence differences between the stationary and non-stationary system estimates followed the parameter changes and did not follow the times corresponding to the imposed ramp. Although there is likely an influence from the position effects, it is much smaller compared with the results from the simulated parameter changes.



Figure 5.10: VAFs between total torque and predicted torques (A, C, E), using the experimental PRBS input with the time-varying system (dashed) and time-invariant system (solid). The total (B), intrinsic (D) and reflex (F) torque variances are plotted for both systems. The short, thick lines indicate when the ramp was imposed in the experimental input. The dashed lines indicate the simulated parameters start and stop.

5.3.4 Model Evaluation

The identification was performed as described in Section 4.1. The chosen IRF lengths were 80 ms, 200 ms, and 400 ms, for intrinsic stiffness, intrinsic compliance and reflex stiffness, respectively. The first 440 ms in time were neglected when plotting the graphs and when calculating mean values across time to eliminate start-up transients.

The mean variances accounted for (VAF) between the predicted and measured torques were computed across the ensemble at each point in time. Figs. 5.11-5.13 display these VAFs across time for each subject. The dashed lines indicate the ramp start and stop. The mean values across time are recorded in each plot.

Similarly to the simulation results using the experimental PRBS input, system estimates at particular times were poor. These results were substantially noisier than those obtained during the simulations. The system estimates at these times were inaccurate and therefore not included in the results. Data at times where the VAF_{total} was less than zero were removed. Subject A had the fewest points removed, whereas Subject C had the most removed.



Figure 5.11: VAF between total and predicted torques; dashed lines indicate start and stop of ramp; Subject A.



Figure 5.12: VAF between total and predicted torques; dashed lines indicate start and stop of ramp; Subject B.



Figure 5.13: VAF between total and predicted torques; dashed lines indicate start and stop of ramp; Subject C.

For Subject A, the VAF_{intrinsic} (B) decreased during the ramp while the VAF_{reflex} (C) increased slightly. This drop in VAF_{intrinsic} and rise in VAF_{reflex} occurred mid-ramp for Subject A. The VAF_{total} (A) dropped throughout the ramp and averaged across time at approximately 70%. The model did not describe the data well, yet Subject A had the best results of all subjects.

For both Subjects B and C, the estimates were worse throughout the ramp. The same trend as in Subject A for the VAF_{total} was found in Subject B, however Subject C showed the opposite, an increase in VAF_{total} during the ramp. The data from Subject C accounted for the least amount of the total torque as compared with Subjects A and B, and is therefore the least dependable data set.

The system estimates did not well describe the data for Subject A, with mean VAF_{total} ranging from 64-70%. In time-invariant experiments using PRBS inputs, generally 85-95% of the total torque variance is accounted for by the model. The reflex torque accounted for less of the total torque than in the simulations, with mean VAF_{reflex} ranging from 8-17%, for Subject A.

To get a sense of how well the identification predicted the torque, the actual recorded torque and predicted net torque traces are plotted in Figs. 5.14 and 5.15. A comparison between the actual and predicted net torque was done for individual trials in Fig. 5.14, but neglecting the times where the model estimates were poor. The trials for Subject A had VAF_{realiz} ranging from 54-89% and the average across all trials was 58%. Subject C had the largest variations in performance with VAF_{realiz} ranging from 26-72%. This shows the variability between trials, perhaps due to changes in the subject's behaviour during the experimental protocol. Since the system estimates are so poor, it is likely a combination of the subject and estimation itself.

Similarly, Fig. 5.15 shows the comparison between the true and predicted torques across the ensemble at three different times. For Subject A the VAF_{total} are similar for the three times and have an average of 70%. Subject C again displayed the poorest prediction, with VAF_{total} ranging from 59-73%. The technique was able to capture joint dynamics across time; however the VAF_{total} are still not as high as for the simulations or studies done using the time-invariant algorithm.



Figure 5.14: Actual total torque (plus) and net predicted torque (points) for three realizations for all subjects.



Figure 5.15: Actual total torque (solid) and net predicted torque (dashed) at three times for all subjects.

5.3.5 Estimated System Dynamics

To view the changes in the dynamics occurring throughout the movement, the systems were plotted at specific points in time, as shown in Figs. 5.16-18. These times were chosen where the model was well predicted (>80%) and a parametric model was well fit (>83%) and were different for each subject. The intrinsic compliance (B) and reflex stiffness (D) were plotted with their respective parametric fit.



Figure 5.16: Estimated IRFs and SNLs at particular times across the ramp; Lines with no markers indicate parametric fits; Intrinsic IRFs (A,B); Hammerstein (C,D); Subject A



Figure 5.17: Estimated IRFs and SNLs at particular points across the ramp; Lines with no markers indicate parametric fits; Intrinsic IRFs (A,B); Hammerstein (C,D); Subject B



Figure 5.18: Estimated IRFs and SNLs at particular points across the ramp; Lines with no markers indicate parametric fits; Intrinsic IRFs (A,B); Hammerstein (C,D); Subject C.

It can be seen from the intrinsic plots in Figs. 5.16-18 that for all three subjects there was an increase in intrinsic stiffness (thus a decrease in intrinsic compliance) across time. This trend was most apparent in Subjects A and C. The parametric fits for the intrinsic compliance were much better prior to the ramp for all subjects, as previously noted from the VAF_{fit}.

The reflex stiffness also increased slightly during the ramp, as seen in the reflex stiffness IRFs for Subjects A and B. We expected the reflexes to be larger after the ramp, since the ankle was in a more dorsiflexed position, corresponding to the subject's optimal operating position (OOP). However the estimated models for the reflex stiffness system were clearly not well modelled by a 2^{nd} order parametric fit. Therefore the changes in the reflex dynamics across time are unclear.

The Hammerstein systems were filtered before fitting the parametric model. The filtering reduces the high frequency noise in the system estimates, but negatively affects the reflex delay. This is seen in Figs. 5.16-18 as some of the reflex stiffness estimates do not show the flat response of the reflex delay, although it is captured in the parametric fits.

The subjects displayed similar behaviour but at different times after the ramp initiation. Subject A exhibited the highest reflex mid-ramp, whereas Subjects B and C showed more reflex activity at the end of the ramp. Thus it appears that Subject A reaches peak reflex activity earlier than the other two subjects. This same trend occurred for Subject A in a preliminary trial using a larger ramp amplitude.

5.3.6 Parametric Models

Parametric models were fit to the filtered intrinsic compliance and reflex stiffness systems. First, the least-squares fitting algorithm was run with an initial estimate. Then the parameters which had the highest VAF_{fit} , at the point in time before the ramp onset, were used again in the algorithm. If there was no significant increase in the maximum VAF_{fit} , then these parameters were used as the best initial guess. Finally the fitting algorithm proceeded as outlined in Chapter 4, with the next system's initial guess being set to previously estimated parameters with a VAF_{fit} greater than 80%.

The parametric fits for the intrinsic compliance were better than for reflex stiffness; however they both were not well modelled by the 2^{nd} order models. In the subsequent plots, only model parameters are shown whose VAF_{fit} was greater than 83%.

Figs. 5.19-5.21 show the estimated parameters from the 2^{nd} order parametric fits and the associated VAF_{fit} for each subject. The intrinsic compliance parameters (K, B, I) are shown in plots G, E, C and the reflex stiffness parameters (G, w, z) are shown in plots D, F, H. Overall reflex gain (G) was calculated as in Chapter 4. The dashed lines indicated the ramp start and stop times.



Figure 5.19: Parameters K, B, I from the intrinsic compliance fits (G,E,C) and G, w, z from the reflex stiffness fits (D,F,H), across time; Dashed lines indicate ramp start and stop; Subject A



Figure 5.20: Parameters K, B, I from the intrinsic compliance fits (G,E,C) and G, w, z from the reflex stiffness fits (D,F,H), across time; Dashed lines indicate ramp start and stop; Subject B



Figure 5.21: Parameters K, B, I from the intrinsic compliance fits (G,E,C) and G, w, z from the reflex stiffness fits (D,F,H), across time; Dashed lines indicate ramp start and stop; Subject C.

The majority of the 'best-fits' to the intrinsic model occurred before the ramp. The parameters remained roughly stable in time for all subjects, as expected. The values then increased throughout the ramp, although limited good data points were available. The changes are significant, as much as 3 times the initial values before the ramp for all parameters. An increase in intrinsic stiffness with increased dorsiflexion does hold true to actual ankle dynamics. The large changes in inertia were surprising as normally it changes very little and likely indicates problems.

The reflex stiffness parameters, on the other hand, displayed very inconclusive findings. This is due to the poorly estimated systems demonstrated by the huge variability of the VAF_{fit} across time, leaving very few 'good-fit' parameters. Thus these parametric models of reflex stiffness are not representative of the true reflex dynamics. A key issue,

which is discussed in Section 5.4, is whether these difficulties are due to the fitting paradigm itself or the poor IRF estimates.

5.3.7 Stationary Studies

Control trials were recorded with only the PRBS perturbation applied to the ankle at specific positions throughout the ramp. The stationary control perturbation trials confirmed that each subject exhibited reflex activity at points throughout the ramp. The estimated VTQ_{IRFs} from these trials for each subject at the ramp start and end positions are plotted in Fig. 5.22.

Reflex stiffness increased as the ankle was more dorsiflexed for all subjects. These trials accounted for much of the torque, demonstrating that the system estimates described the data well. For Subject C at the ramp end, 20% of the VAF was attributed to reflex torque, with a VAF_{total} of 85%. Similarly for Subject B at the ramp end, VAF_{reflex} was 20% and VAF_{total} was 76%.

The control perturbation trials for Subject A were surprising as only 1% of the VAF was attributed to reflex torque, at ramp end, with high a VAF_{total} of 94%. The pulse trials for Subject A showed much larger reflex torques at the ramp end position, as well as in previous PRBS trials for this subject in pilot experiments. It is likely that these experiments were not typical behaviour for Subject A.



Figure 5.22: VTQ_{IRF} estimates from the stationary, control perturbation trials at ramp start (dashed) and end (solid) positions for Subject A (A), B (B) and C (C).

The poor system estimates at certain times may be due to the lack of a rich signal from the ensemble input. To further investigate this statement, a test was performed with the stationary algorithm using the control perturbation trial at the ramp mid-point for Subject C. The stationary algorithm was applied to various segments of the data, 4 seconds in length (400 points), and also to the entire data set, 30 seconds in length (3,000 points). This compares to the ensemble time-varying technique estimating across the ensemble of 400 realizations at each time.

The resulting reflex stiffness estimates are shown in Fig. 5.23. The system estimates do vary from one segment to another and deviate from the 'best' estimate utilizing 30 seconds of data. This supports the conclusion that the input may not be rich

enough for good identification using the 400 realizations with the ensemble time-varying algorithm. If more points do improve the estimates, then future work should involve testing PRBS inputs using 4000 realizations rather than 400, in simulation studies.



Figure 5.23: VTQ_{IRF} estimates utilizing different segments of data from the stationary, control perturbation trial at mid-ramp for Subject C.

As the system estimates and parametric fits were poor certain times, an accurate comparison cannot be made between the stationary results and the time-varying results. The overall stiffness increased as the foot was more dorsiflexed for all subjects under both stationary and time-varying conditions, but as mentioned, there were too many times at which the system estimates were poor for the time-varying trials.

Previous work has illustrated that it is not reasonable to assume properties of joint dynamics occurring during movement will correspond to those obtained at equivalent operating points during time-invariant conditions [19, 29]. This advocates further development of such novel time-varying identification methods to gain a better understanding of joint mechanics during movement.

5.4 Discussion

A major finding of the present work is that the time-varying stiffness identification did not work very well with the inputs we used experimentally. This limitation for the algorithm is discussed and potential improvements presented. The resulting system dynamics are briefly presented as well as future improvements to the experimental protocol.

5.4.1 Results

The time-varying identification algorithm was applied to experimental data acquired from three subjects, whose ankle underwent a large stretch in dorsiflexion. This stretch produced a significant increase in the joint torque but had little effect on the GS EMG, due to the slow speed of the ramp. Descriptions of the instantaneous stiffness dynamics were obtained throughout the movement at a time resolution equal to the sampling rate, by using the torque responses evoked by the small amplitude PRBS perturbations superimposed on the larger amplitude stretch.

Given the results from stationary conditions, it was expected that overall joint stiffness would increase from a position of plantarflexion to a stretched position of dorsiflexion. This was consistently shown in all subjects. The reflex stiffness did increase during the ramp, particularly for Subject A, which may support the stance that reflex modulation plays a role in initiating and/or controlling voluntary movements. However it was not possible to make concrete conclusions on the role of the stretch reflex during this movement, as the estimation of the reflex pathway was poor and the overall total variance accounted for was significantly lower than achieved in simulations or in time-invariant situations.

All subjects showed the similar trend in intrinsic stiffness and reflex stiffness with time. The ensemble torque and GS EMG for all subjects was also similar. This demonstrates that the experiments were performed in the same manner so that the resulting behaviour was not widely different between subjects.

5.4.2 Identification Algorithm

The algorithm performed very well in the simulations using the Gaussian input. Using the experimental PRBS input, it also performed well, however not at all times. The algorithm did not function at all using a computer-generated PRBS input. Using the experimental data, the algorithm produced good estimates at some times and not at others. This consistent behaviour from simulation to experiments suggests the algorithm's deficiency in handling PRBS inputs.

As the ensemble techniques utilize the data across the ensemble at specific points in time, there may be times at which the ensemble input is not rich enough to permit a good identification. The ensemble time-varying identification algorithm estimates across the ensemble and therefore is limited by the number of trials obtained. Under stationary conditions, the time-invariant technique generally uses 10 times the number of points as used in the ensemble algorithm. The stationary identification was tested using fewer points and found to have variable system estimates. Thus the identification techniques do require an input signal with enough information to permit good identification. The challenge associated with the ensemble time-varying algorithm is that more than 400 realizations obtained in a session may fatigue the subject. For future investigations, the simulation should be run with over 4000 realizations of the PRBS input to see whether the estimates improve.

Gaussian perturbations have much wider position and velocity probability distributions than PRBS, and therefore provide an ensemble input that is rich enough to permit good identification. Other inputs should be investigated with the simulation, such as multi-level (amplitude) PRBS filtered inputs or PRBS inputs with superimposed small amplitude Gaussian noise. Both the position and velocity distribution must be wider than with the PRBS inputs. However it is equally important that these inputs elicit reflex responses.

The identification showed substantial evidence of estimating the intrinsic component of stiffness; however it failed to provide a good evaluation of the reflex component. This may lead to an overestimate of the amount of torque attributed to the intrinsic mechanics. There may have been excess noise in the data, which contributed to these poor results. Noise reduction methods for implementation into the algorithm should be investigated.

Parametric 2^{nd} order models were fit to the data. Very few parametric models had a high VAF_{fit}, particularly for reflex stiffness. The question arises whether the fitting issues are a result of the fitting paradigm itself or due to the poor IRF estimates or a combination? The least-squares method does require good initial estimates to function properly and this may have contributed to the poor fits. An improved approach would have been to utilize the estimated parameters from the stationary control trials as initial estimates, specific for each subject. Alternative fitting paradigms should also be considered, rather than relying solely on the least-squares method. Although not examined in detail, the VAF_{fit} and VAF_{TQ} did correlate in most cases (i.e. both low at certain times). Thus, poor system estimates were likely the major contributor to the poor parametric fits. However another consideration is that the stiffness models themselves may not be well represented by 2nd order models, as we assumed, particularly throughout the ramp movement. Previous work has shown that third order fits were necessary at some ankle positions, and particularly for reflex stiffness IRFs at high levels of contraction [57].

Further investigations could search for a suitable input, with low mean absolute velocity and a wider velocity distribution to excite the reflex pathway and provide a large input range to identify the SNL; however this may still not guarantee good identification. Recent work published by Dempsey and Westwick [58], utilized cubic splines instead of polynomials to represent the SNL. They found much better estimates at corners and edges of the SNL using cubic splines than using polynomials. This may provide a better estimation of the nonlinear component in the Hammerstein system.

One key assumption was the choice of model structure. Although it has been successful under various stationary conditions, the parallel-cascade model structure may not represent ankle joint dynamics during this imposed stretch or potentially during any movements. During movements or conditions where the dynamics change rapidly, the parallel-cascade model may be too simplistic. Kirsch and Kearney [57] concluded that a more complex model of joint stiffness is likely required to describe the nonstationary changes occurring in joint stiffness during this imposed movement. The algorithm worked

well in the simulations but this was only for a given set of conditions. A more appropriate model structure may have to be considered for time-varying tasks and this could lead to the development of new identification algorithms; however this is beyond the scope of this work.

5.4.3 Methodology Considerations

Improvements were made to the previous experimental protocol to reflect more recent studies in our laboratory [3, 4]. The differences between the previous study [41] and the current experimental paradigm are outlined in Table 5.3.

	Previous Study [41]	Current Study
Input Perturbation	Gaussian filtered	PRBS Smaller DMS value its [2]
	 Larger RMS velocity Power at high frequencies	 Smaller RMS velocity [3] Power at lower frequencies
Ramp End Position	• 0.13 radians from neutral position	• At OOP, where largest reflex torque (depends on subject)
Analysis Technique	• Ensemble time-varying identification using SVD and least-squares method [33]	• Ensemble time-varying, parallel- cascade identification algorithm based on Lortie's techniques [4]
Reflex Stiffness IRF	• Between velocity and GS EMG	• Between velocity and reflex torque

 Table 5.3: Comparison of Experimental Protocols

The reflex activity was significantly enhanced using the PRBS perturbation inputs with a low mean absolute velocity and power at lower frequencies, as determined in a study by Kearney, Stein and Parameswaran [3]. The filtered Gaussian inputs previously used were found to suppress reflexes. Similarly, utilizing pulse trials to determine the optimal operating position (OOP), as performed by Tung [50], ensured significant reflex activity at the ramp end position.

The recent identification techniques by Lortie [4] imposed fewer restrictions and provided better estimates than MacNeil's [33] in the presence of significant output noise. Most previous studies of reflex modulation during movement only examined EMG, as in [41], which is why our protocol reflects the mechanics of the joint during movement by computing the reflex stiffness IRF between velocity and reflex torque.

The time-varying ensemble technique requires identical behaviour from one realization to the next to produce the most accurate results. There are many sources of trial-to-trial variability, such as the subject, the data acquisition and protocol. The subject may adjust their body position, initial contraction level, and voluntary reaction to the imposed ramp from one realization to the next. These may affect their ankle joint dynamics.

A post-processing selection procedure was used to account for the subject's contraction level, by examining the standard deviation of the torque for each realization (Section 5.2.1). Trials were aligned according to the ramp start, but this depends on the timing of the acquisition of only the ramp input compared with the acquisition of the actual position. There may have been slight timing discrepancies within a trial thus affecting the alignment procedure.

An important consideration for the protocol was that the ramp occurred at random times with respect to the superimposed perturbations and that the subject had no warning that a ramp was about to be imposed. Thus, the experimental protocol was setup such that the subject had to re-establish the torque level before another ramp stretch was initiated. The torque level had to be matched to within $\pm 10\%$, and often subjects would become very good at re-establishing the torque after many realizations. Therefore there may have been some prediction by subjects who were able to maintain the target torque level immediately after the plantarflexing ramp returned their foot to the initial position. A solution would have been to put a pause after each ramp of random length (i.e. between 0-2 s). However the entire protocol already lasted for 4 hours, so any additional time spent in the actuator fatigues the subject and may also cause changes in their joint dynamics.

Another methodological consideration not addressed in the analysis of the results was to utilize the reflex EMG dynamics to determine a subject-specific reflex delay. The reflex delay is used to limit the intrinsic stiffness IRF length so that during identification any reflex contributions are neglected due to this timing discrepancy. For simplicity, we utilized 40 ms for all subjects. This is not a significant issue in this study, as the reflex EMG dynamics were briefly examined and all subjects had reflex delays around 40 ms; however this step should be integrated into the algorithm for future use. Although the ensemble mean position was removed from each position record, there were some changes in the properties of the perturbation during the time of the imposed ramp. We tested the potential effect of these changes on the identification procedure and found that they had little effect on the estimation results. Nevertheless, for future work, it would be beneficial to eliminate this effect or fully account for and understand these effects.

5.4.4 Summary

A new method for time-varying identification of joint dynamics has been developed and preliminary tested. It was capable of estimating the intrinsic mechanics at the ankle joint, with results similar to those found in a similar study [59]. Estimates of reflex dynamics were unreliable, as the variance accounted for was significantly low and a second-order mechanical model was not well fit to the data, even at time-invariant conditions. Future steps have been discussed to evaluate how the algorithm and the experiments can be improved to achieve reliable estimates for ankle stiffness using PRBS inputs.

6. Conclusion

A method was developed to identify time-varying systems. The algorithm was tested using simulated and experimental data. The results, a brief discussion and suggestions for future work are presented.

6.1 Results

The algorithm was capable of identifying a simulated time-varying system very well using Gaussian inputs. Experimental PRBS position records were applied as input to the simulation. These results showed good estimates at certain times and poor estimates at others.

Joint position and torque data was acquired from three subjects while their ankle underwent a large dorsiflexing stretch with superimposed PRBS perturbations. The system estimates described the data fairly well at certain times and very poorly at others. Based on the good system estimates, the intrinsic and reflex stiffness were found to increase throughout the movement. Reflex stiffness and intrinsic compliance models were not well modelled by a 2nd order mechanical model at most times.

6.2 Discussion

The parallel-cascade model was adapted to be used under time-varying conditions. From simulation and experimental studies, the algorithm was not capable of providing good system estimates at all times using PRBS inputs.

Since the results were positive at all times using Gaussian inputs to the simulation, one possible explanation is that the ensemble input did not provide a signal rich enough to permit a good identification. The PRBS inputs do have characteristics that provide less information, in terms of position and velocity distributions, as compared with Gaussian inputs.

A major assumption that may have been violated during the imposed stretch is that of the parallel-cascade model. The description of the intrinsic and reflex stiffness pathways may be entirely different and more complex during movement.

Although a time-varying, parallel-cascade identification algorithm has been developed, there are many areas for improvements. The major finding from this work was

that the algorithm works poorly with this PRBS input. The parallel-cascade structure and algorithms require a thorough review, and can be further tested in simulations at different conditions. Different parametric model structures may apply during movement, as the 2nd order fits were not good. Alternative parametric fitting methods should also be examined. Since some estimates were good at some times and not at others, the properties of the input across the ensemble must be further inspected. Investigations could utilize different inputs, first with the simulation and then with experiments, to potentially obtain better estimates at all times.

In the long term, the study of voluntary movement will require additional efforts. The actuator will have to operate in a closed-loop manner. Therefore closed-loop identification methods will have to be integrated into the time-varying algorithms. In spite of the long journey ahead, this work has brought the study of voluntary movement one step closer to reality, as the time-varying nature of systems can be isolated and the mechanical consequences of reflex activity during time-varying behaviour can be examined.

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Appendices

A. Axis of Rotation

Figure A.1 illustrates the position of the axis of rotation on the lateral side of the ankle joint, with respect to the lateral malleolus, as obtained from anthropometric data [3.1]. Figure A.2 illustrates the position of the axis of rotation on the medial aspect of the ankle with respect to the medial malleolus. The histograms in each figure indicate the number of specimens tested.



Figure A.1: Location of ankle axis of rotation with respect to most lateral point of the lateral malleolus


Figure A.2: Location of ankle axis of rotation with respect to most medial point of the medial malleolus

B. Identification Implementation

An object oriented matlab tool box for linear and nonlinear system identification has been developed in our laboratory [60]. This toolbox was used to generate the time-varying model objects. The class at the top of this object oriented toolbox is called *nltop* (top of nonlinear class) and is divided into various subclasses, one of which is *nldat* (nonlinear data) object types. The time-varying model objects (*tvm*) used for this thesis are of type *nldat* and thus inherit all the methods from its derived classes (*nldat* and *nltop*).

Many methods existed specifically for the *tvm* objects and some of these call on methods from other model types, such as *irfs* and *polynomials* types. Certain methods were edited for this thesis, such as *plot* (to allow more flexibility when plotting objects of type *tvm*), and *nlident* (to appropriately set certain parameters such as the start time, when performing time-varying identification). Methods that were added for use with the time-varying, parallel-cascade algorithm included tv_irf_fit (which fit parametric models to time-varying objects), and *propagate* (which performed the propagation of the IRFs, described in Section 4.1.1.2). A function called $tv_2_LP_delay$ was created to generate a time-varying impulse response of 2^{nd} order low-pass filters in series with a delay, for the simulation. Similarly for simulation purposes, a function called vaf_irf which computed the VAF between two IRFs and two SNLs was created to allow comparison between the simulated and identified time-varying systems.

C. Time-Varying Parallel-Cascade Identification MATLAB Code

```
% tvident data.m
2
% This script is used to run time-varying identification to identify
% ankle dynamics from ensemble experimental data.
8
% The format follows the parallel-cascade algorithm as developed for the
% time-invariant case (i.e. see reflex stiffness.m)
2
% IN WORKSPACE:
               - Must have an nldat object named 'XS' (created from
응
90
                 tvselect.m)
               - 'XS' should be a 3D nldat object with the following
응
S
                 structure: [:,5,:], where the first coordinate
                 represents time, the second is the five channels
8
응
                 recorded in this order (POS, TQ, TA EMG, GS EMG, INP),
ę
                and the last is realizations
응
% SET PATHS:
8
               - Must include the path where propagate.m is located
90
                 (CHANGE THE FIRST LINE OF CODE AS NECESSARY)
8
% MJB May 18/04
% MJB Oct 19/04 Add comments
%Must include in path location of propagate.m
addpath P:\Thesis\Simulations\Time varying\simulate
%User selection of IRF lengths (NLags) for intrinsic stiffness,
%intrinsic compliance & reflex stiffness IRFs
disp(' '); disp([ 'The length of interest of the data is ' num2str( ...
        (size(XS,1)) * (get(XS,'domainincr')) * 1000) ' milliseconds']);
```

```
disp('Choose the NLags accordingly to the length of data ...');
h_int = input('Enter NLags for intrinsic IRFs (ms):');
h comp = input('Enter NLags for compliance IRFs (ms):');
h ref = input('Enter NLags for reflex IRFs (ms):');
%User selection of a decimation ratio
dratio = input('Enter decimation ratio (if no decimation enter 0):');
%The ensemble mean must be calculated for the newly selected trials
%(lost trials in tvselect.m)
XM=mean(XS,3); %Ensemble mean for each channel
XR=XS-XM; %Removed the ensemble mean
if dratio ~= 0 %DECIMATION
    disp(['Decimating the data ...']); disp(' ');
    Vel = ddt(XR(:,1,:)); %Velocity before decimation
    XRD=decimate(XR,dratio);
    V = decimate(Vel,dratio); %Velocity after decimation
    disp(['... finished decimating.']); disp(' ');
else %NO DECIMATION
    XRD=XR;
end
%Calculate the new sampling frequency, time vector & NLags for IRFs
%after decimation.
fs new = 1/get(XRD, 'domainincr');
time start = get(XS, 'DomainStart');
time = [time_start : 1/fs new : time start + ...
        (size(XRD,1)/fs new - 1/fs new)];
nsamp = length(time); %Define the number of samples
h int = fix(h int/1000*fs new);
h comp = fix(h comp/1000*fs new);
h ref = fix(h ref/1000*fs new);
% Use white noise input to find inverse of intrinsic stiffness (compl.)
INP matrix = [];
AMP = input d('Enter amplitude for Gaussian position input to find ...
noise-free torque [for compliance] (rad)',0.03,0.00001,1);
fc pos = input d('Enter the cutoff frequency or 0 (zero) for no filter
(Hz)',0,0,fs);
for i=1:num trials
INP = AMP/2*randn(length(time),1);
if fc pos \sim = 0
[C1,A1] = butter(1,fc pos/(fs/2)); %LP filter
      INP = filter(C1,A1,INP);
end
INP matrix = [INP matrix INP];
end
INP matrix = reshape(INP matrix,length(time),1,i);
INP matrix = nldat(INP matrix, 'domainincr',ts);
TQ = XRD(:,2,:); %Recorded total torque
POS = XRD(:,1,:); %Recorded Position
%Initialization of parameters for identification loop
```

```
vaf total = 0; %VAF estimate
vaf last = -1; %VAF previous estimate
icount = 0; %Number of iterations
TQ R pred = nldat(0); %Predicted reflex torque
TQ R res = TQ - TQ R pred; %Initial estimate of Reflex residual torque
figure; %All plots will be generated on the same figure
disp(' '); disp('IDENTIFICATION commencing ...'); disp(' ');
% ITERATE UNTIL VAF TOTAL DOES NOT IMPROVE ANYMORE
while vaf total > vaf last
    vaf_last = vaf_total; %Set to previous VAF estimate
    icount = icount + 1; %Increase number of loop iterations by 1
                 ITERATION = ' int2str(icount)])
    disp(['
    % Identify intrinsic pathway
    8 {{{
    disp(' '); disp('Identifying Intrinsic stiffness ...')
    %Intrinsic Stiffness IRF to be estimated between POS & TQ R res
    Zstiff = cat(2,POS,TQ_R_res);
    %Linear dynamic 2-sided Intrinsic Stiffness estimated using
    %pseudoinverse method
    istiff=tvm(Zstiff,'Model Type','irf','Nsides',2,'nlags', ...
        (h int+1), 'Method', 'pseudo', 'comment', 'PTQ I R F');
    clf; plot(istiff); title('PTQ I R F')
    disp(' '); disp(['PAUSE ... until you hit a key']); disp(' ');
    pause
    %Propagation of IRFs
    istiff = propagate(istiff);
    disp(' '); disp(['PAUSE ... until you hit a key']); disp(' ');
    pause
    disp(' '); disp('Identifying Intrinsic Compliance ...')
    %Estimation of Intrinsic Compliance between TQ R res & POS
    % Generate TQ based on intrinsic stiffness IRF, using a noise-free
    % pos.input
    OUT = nlsim ( istiff, INP matrix );
    Zcomp = cat(2,OUT,INP matrix);
    icomp = tvm(Zcomp, 'Model Type', 'irf', 'Nsides', 1, 'nlags', (h comp), ...
        'Method','pseudo','comment','TQP_I_R_F');
    clf; plot(icomp); title('TQP I R F')
    disp(['PAUSE ... until you hit a key']); disp(' '); pause
    %Propagation of IRFs
    icomp = propagate(icomp);
    %Smoothing filter (1 pass) using a 3-point moving average algorithm
    icomp = smo(icomp, 1);
    clf; plot(icomp); title('TQP I R F')
    disp(' '); disp(['PAUSE ... until you hit a key']); pause
```

%Time-varying convolution of Intrinsic Stiffness (istiff) with %Position (POS) to get an estimate of intrinsic torque (TQ I pred) [TQ I res, istiff vaf, TQ I pred] = nlid resid(istiff,... cat(2, POS - mean(POS), TQ), 1);%[output residual, irf vaf, predicted output] = nlid resid(irf, %cat(2, data to convolve with irf, data to compare with predicted %output), flag to stop plotting function); disp(' '); disp('...identification of Intrinsic pathway finished.') 8 {{{ % Identify reflex pathway 8 { { { disp(' '); disp('Identifying Reflex pathway ...') %Concatenate Velocity & Intrinsic Residual Torque (==TQ - TQ I pred) ZVTQ=cat(2,V,TQ_I_res); %Using velocity as input and the intrinsic residual torque as output %(reflex torque estimate), the static nonlinearity and linear %dynamic elements in the reflex pathway are estimated using the %Hammerstein identification procedure. ihammer = tvm(ZVTQ,'Model Type','nlbl','Nsides',1,'nlags',h ref,... 'ordermax',3,'comment','VTQ irf'); %'nlbl' => nonlinear block structure model type %'ordermax' => Maximum polynomial order estimated %To filter VTQirf once, a 3-point moving average is used ihammer = smo(ihammer,1); %Convolve Hammerstein system with velocity to get an estimate of %reflex torque. Reflex residual torque (TQ R res = TQ - TQ R pred). [TQ_R_res, ihammer_vtq_vaf, TQ_R_pred] = nlid_resid(ihammer_vtq,... cat(2, V, TQ),1); %Normalize identified Hammerstein system; gain is redistributed %between nonlinear and linear subsystems ihammer old = ihammer; ihammer = normalize(ihammer,1); %DC gain of IRF is unity clf; plot(ihammer vtq); disp(' '); disp(['PAUSE ... until you hit a key']); pause disp(' '); disp('... identification of Reflex pathway finished.') 8 { { { %Calculation of Voluntary torque offset OFFSET = mean(TQ) - mean(TQ R pred); %Means for each realization %Convert OFFSET nldat object to double so that it can be added %properly to other nldat objects. offset data = OFFSET.data; offset data = reshape(offset data,1,... length(OFFSET));

```
off temp = zeros(size(TQ, 1), size(OFFSET, 3));
 for j = 1:size(OFFSET, 3)
     for i = 1:size(TQ, 1)
          %Create matrix of mean values for each realization at each
          %point in time
          off_temp(i,j) = offset_data(j);
      end
 end
 off temp = reshape(off temp, size(TQ, 1), 1, size(OFFSET, 3));
 OFFSET = nldat(off temp);
 %This nldat object can now be added properly to other nldat objects
 %Net predicted torque
   TQ net pred = TQ R pred + TQ I pred + OFFSET;
 disp(' ');
 warning off MATLAB:divideByZero;
 %VAF calculations below may result in division by zero, so warning
 %is turned 'off' to keep command window clear.
 %VAF calculations across the ensemble at each point in time for the
 %predicted torques. **NOTE: mean values are calculated by neglecting
  %times corresponding longest IRF length (h_ref).
%Intrinsic
 vaf int = double(vaf(TQ, TQ I pred, 'sample'));
 mean vaf int = mean(vaf int(h ref:nsamp));
 %nsamp is number of samples
%Reflex
 vaf ref = double(vaf(TQ I res, TQ R pred, 'sample'));
 mean vaf_ref = mean(vaf_ref(h_ref:nsamp));
%Total
 vaf tot = double(vaf(TQ, TQ net pred, 'sample'));
 mean vaf total = mean(vaf tot(h ref:nsamp));
 disp(['===-- VAFs for Iteration ' int2str(icount) ' --==='])
 disp('---VAF torques---')
 disp(['Mean VAF intrinsic: ' num2str(mean vaf int)])
 disp(['Mean VAF reflex: ' num2str(mean vaf ref)])
 disp(['Mean VAF total: ' num2str(mean_vaf_total)])
 clf; subplot(311);
 plot(time(h ref:nsamp), vaf int(h ref:nsamp));
 title('VAF intrinsic'); axis([time(h_ref) time(nsamp) 0 100])
 subplot(312);
 plot(time(h ref:nsamp),vaf ref(h ref:nsamp));
  title('VAF reflex'); axis([time(h ref) time(nsamp) 0 100])
 subplot(313);
 plot(time(h ref:nsamp), vaf tot(h ref:nsamp));
 title('VAF total'); axis([time(h ref) time(nsamp) 0 100])
 disp([' IRF iteration ' int2str(icount) '; Total VAF= ' ...
          num2str(mean_vaf_total)])
  % ITERATE UNTIL VAF TOTAL DOES NOT IMPROVE ANYMORE
 vaf total = chop(mean vaf total,4); %New total VAF
 disp(' '); disp(['PAUSE ... until you hit a key']); disp(' ');
 pause
```

```
end %while loop
disp(' '); disp('Identifying EMG Hammerstein system ...')
%Identify reflex EMG dynamics between Velocity and GS EMG
GS=XRD(:,4,:);
ZR=cat(2,V,abs(GS)); %Concatenate Velocity & rectified GS EMG
% Hammerstein model time-varying identification
ihammer_vgs=tvm(ZR,'Model_Type','nlbl','Nsides',1,'nlags',h_ref,...
    'ordermax',3,'comment','VGS_I_R_F');
clf; plot(smo(ihammer_vgs,2))
disp(' '); disp('... identification of EMG Hammerstein finished.')
disp(' ... IDENTIFICATION finished.')
```

D. Ethics Certificate

Please find attached our Ethics Certificate dated April 5, 2004, valid until April 4, 2005.

Faculty of Medicine 3655 Promenade Sir William Osler Montreal, QC H3G 1Y6 April 6, 2004

Faculté de médecine 3655, Promenade Sir William Osler Montréal, QC, H3G 1Y6

Dr. Robert Kearney McGill University Faculty of Medicine Department of Biomedical Engineering Duff Medical Building, Room 309 3775 University Street Montreal, Quebec H3A 2B4

Dear Dr. Kearney:

We are writing in response to your request for continuing review for the study A04-M09-97 entitled "System Identification of Functional Modulation of Instrinsic and Reflex Studies".

The progress report was reviewed and we are pleased to inform you that **full board re-approval** for the study was provided by the Chair of the Committee on *April 5, 2004*, valid until *April 4, 2005*. The certification of annual review is enclosed.

We ask you to take note of the investigator's responsibility to assure that the current protocol and consent document are deposited on an annual basis with the Research Ethics Board of each hospital where patient enrollment or data collection is conducted.

Should any modification or unanticipated development occur prior to the next review, please advise the IRB promptly.

Yours sincerely,

Lawrence Hutchisoon, M.D. Co-Chair Institutional Review Board

cc: A04-M09-97

McGili Faculty of Ma Institutional Review -Continuing Revi	APPROVAL APPROVAL APR 0 5 2004 W Board Faculty of Medicine
Principal Investigator: <u>Noter Rearriey</u>	Department/institution: <u>Digmedical Engineering</u>
Title of Research Study: <u>A04-M09-97</u> <u>CIHR: System identification of functional modulation of intrin</u> <u>FQRNT: Strategies biomimetiques pour le controle du mouven</u>	<u>nsic and reflex stiffness</u> ment en robotique et en rehabilitation)'
Date of initial IRB approval: <u>4 April 1997</u> Date of previous contin	nuing review (if applicable):
INTERIM REPORT (PLEASE CHECK OR SPECIFY)	
Current Status of Study:	
Active Study: X On Hold:	Closed to Enrolment:
Interim Analysis: Final Analysis:	Study Not Activated*:
McGill hospital(s) where study has received approval of local Hesearch is JGH: D MCH: DMGH: D MNI RVH: D SMH: D Other: D	Ethics Board(s) (if applicable):
McGill hospital(s) where study has not received approval of local Resear	arch Ethics Board(s) (if applicable):
If study sponsorship or financial support has changed, please provide co	orrespondence to explain; enclosed:
Number of subjects to be enrolled at McGill: 10/year Nun	mber of McGill subjects enrolled to date:40
Number of McGill subjects enrolled since last review: Have	e McGill subjects withdrawn from the study?: <u>No</u>
Has the study been revised since the last review?: <u>Yes</u> Have the st	study revisions been approved by the IRB?: <u>Yes</u>
Has the consent form been revised since the last review?: No	_ Date of the current consent form:28 July 2003
Are there new data since the last review that could influence a subject's	willingness to provide continuing consent?: <u>NO</u>
Have all serious adverse experiences (SAEs) and safety reports relevant	nt to the study been reported to the IRB?:YES
SIGNATURES:	
Principal Investigator: Robert Kearney	Date:11 March 2004
	0 5 APR 2004
IHB Chair D)ate:

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