

Kinematic and Dynamic Extraction of Massage Manipulations and Their Reproduction in Robotic Systems: A Clinically Oriented Review with Implications for Dual-Arm Massage Robotics

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Abstract:

Massage and Tuina are widely used in musculoskeletal rehabilitation and supportive care, yet their therapeutic dose remains insufficiently defined in quantitative terms. This review summarizes how massage manipulations can be characterized through kinematic and dynamic variables and how these features may be translated into robotic reproduction, with particular attention to clinically relevant dual-arm systems. A clinically oriented narrative review was conducted across literature on massage therapy, biomechanics, rehabilitation robotics, compliant control, and physical human-robot interaction. Current evidence indicates that massage can be represented by measurable descriptors, including displacement, velocity, force magnitude, impulse, loading rhythm, and contact stability, whereas robotic systems can increasingly reproduce these patterns through force sensing, imitation learning, and adaptive compliance control. Existing studies support the feasibility of robot-assisted massage in low back pain, oral rehabilitation, and wellness-oriented applications, although clinical evidence remains limited and heterogeneous. Overall, the field is moving from simple automation toward standardized and patient-adaptive mechanical therapy. Further progress will depend on quantitative dose definition, safety-aware control, stronger clinical validation, and improved integration of bimanual therapeutic strategies into dual-arm robotic systems.

Keywords:

Massage Therapy, Tuina, Rehabilitation Robotics, Compliant Control, Soft-Tissue Interaction

1. Introduction

Massage and related manual therapies remain important nonpharmacological interventions in rehabilitation medicine, pain management, and supportive care. They are widely applied in patients with low back pain, neck pain, myofascial disorders, temporomandibular disorders, and stress-related conditions [1-12]. Their enduring clinical relevance reflects several practical advantages: they are noninvasive, adaptable to different care settings, and readily combined with exercise-based or multidisciplinary rehabilitation. In routine practice, massage is valued not only for symptom relief but also for promoting relaxation, improving comfort, and facilitating functional recovery.

Despite this clinical relevance, massage remains insufficiently standardized as a therapeutic intervention. Pharmacological treatment is typically described through dose, route, and frequency, whereas massage is often defined only by technique name, treatment duration, or practitioner experience. Such descriptions do not adequately capture the physical stimulus delivered to tissue. Key variables, including force magnitude, loading direction, contact area, temporal rhythm, spatial coverage, and tissue response, are frequently omitted or inconsistently reported. As a result, two interventions labeled with the same technique may differ substantially in their biomechanical characteristics, thereby limiting reproducibility across therapists, studies, and clinical settings.

This limitation becomes particularly important when massage is considered from the perspective of robotic reproduction. A robot cannot reproduce a therapeutic manipulation in a meaningful way unless that manipulation has first been represented as a measurable and transferable pattern. Recent advances in biomechanical sensing, learning from demonstration, force regulation, and physical human-robot interaction have made it increasingly feasible to quantify massage in terms of motion and force and to map these descriptors onto robotic execution [23-35,65-79]. In parallel, massage-specific robotic systems have evolved from simple mechanotherapy devices toward platforms capable of force sensing, compliant interaction, trajectory planning, and adaptive control [36-54]. These developments suggest that massage can increasingly be treated not only as a traditional therapeutic skill but also as a structured mechanical intervention that can be extracted, modeled, and reproduced.

Accordingly, this review provides a clinically oriented synthesis of current knowledge on the kinematic and dynamic extraction of massage manipulations and their robotic reproduction. Particular emphasis is placed on the biomechanical basis of massage, the quantitative description of therapist skill, the translational logic of robotic implementation, and the potential role of dual-arm systems in reproducing bimanual therapeutic strategies. The central premise is that the future of massage robotics lies not in superficial imitation of human movement, but in rigorous dose definition, stable tissue interaction, and meaningful clinical validation.

2. Clinical and Biomechanical Foundations of Massage Manipulation

Massage should be understood as a controlled mechanical interaction between the practitioner and a deformable biological target. Skin, subcutaneous tissue, fascia, and muscle do not behave as rigid structures; rather, they exhibit nonlinear, viscoelastic, anisotropic, and history-dependent behavior [19,33,34,35]. Consequently, the same nominal hand movement may generate different internal tissue responses depending on local stiffness, body contour, frictional conditions, hydration, muscle tone, and

patient sensitivity. From a mechanistic perspective, massage is therefore not merely a visible manual action but a time-dependent mechanical stimulus whose biological effect emerges through tissue interaction.

This view has two immediate clinical implications. First, therapeutic effect depends not only on the named technique but also on the manner in which the load is applied. A slowly applied sustained compression differs fundamentally from a brief impulse, even when peak force is similar. Likewise, rolling, kneading, vibration, and percussion differ in temporal organization, waveform regularity, loading rate, and distribution of force over time. Second, massage is inherently multidimensional. Experimental studies have shown that manual contact involves not only normal compression but also tangential loading, shifting force vectors, continuous pressure modulation, and adaptive response to tissue feedback [23,24,25]. In practice, therapists do not simply press downward; they glide, stabilize, tension, release, oscillate, and redirect force according to both anatomy and tactile judgment.

For this reason, massage dose should be defined using more than technique labels alone. At a minimum, a clinically meaningful description should include contact location, contact area, loading direction, force amplitude, temporal rhythm, and treatment duration. Depending on the therapeutic objective, additional variables such as spatial coverage, impulse, loading rate, duty cycle, release-to-load ratio, and cycle regularity may also be required. This multidimensional perspective is especially relevant in Tuina and related manual traditions, in which named manipulations represent families of coordinated biomechanical actions rather than fixed, invariant motions [11,12,13,14,29,30].

This framework also helps explain why current clinical evidence, although promising in several musculoskeletal conditions, remains difficult to compare across studies. Reviews of massage and Tuina in low back pain, neck pain, and related disorders suggest potential benefit, but also highlight substantial variation in intervention content, dose reporting, and outcome selection [1-12]. Without more precise characterization of the delivered mechanical exposure, dose-response interpretation remains limited. Quantitative massage science is therefore not only an engineering requirement but also a medical one.

Table 1. *Clinical and biomechanical characteristics of representative massage manipulations.*

Manipulation type	Main clinical purpose	Dominant kinematic features	Dominant dynamic features	Likely robotic reproduction requirement
Pressing	Trigger-point release, deep tissue compression, analgesia	Small displacement, sustained contact, low trajectory complexity	High normal force, long dwell time, slow loading-unloading cycle	Accurate normal-force control and compliant vertical interaction
Kneading	Soft-tissue relaxation, circulation enhancement	Cyclic local motion with coupled rotation/translation	Moderate force, repeated loading, combined normal and shear components	Multi-axis contact control and stable local trajectory generation
Rolling	Broad tissue mobilization, paraspinal treatment	Continuous rhythmic trajectory, relatively large	Periodic force waveform, moderate amplitude,	Smooth trajectory tracking with stable rhythmic

		coverage area	frequency-sensitive	force output
Friction	Fascial mobilization, localized tissue release	Short directional displacement, repeated sliding	Relatively high shear component, moderate normal preload	Shear-aware control and friction-adaptive contact regulation
Vibration	Neuromuscular modulation, relaxation	Small-amplitude oscillatory movement	High-frequency low-amplitude force oscillation	High-bandwidth actuation and oscillation stability
Percussion/beating	Rhythmic stimulation	Repetitive impulsive motion, brief contact events	Short-duration high-peak impulses, high loading rate	Accurate timing control and safe impact limitation

Table 1 underscores a key translational principle: massage manipulations are distinguished not simply by how they look, but by how motion and force are organized over time. This distinction is fundamental when human therapeutic skill is to be encoded for robotic execution.

3. Quantitative Extraction of Massage Kinematics and Dynamics

The translation of massage into robotics begins with quantitative extraction of expert manipulation. In this context, kinematic extraction describes how the therapist moves, whereas dynamic extraction describes the load delivered to tissue over time. Both are essential, because neither movement alone nor force alone adequately defines massage as a therapeutic exposure.

Kinematic descriptors typically include displacement, trajectory, velocity, acceleration, orientation, coverage area, repetition period, and curvature of motion [26-30]. In massage, these variables should be considered at more than one scale. At a global scale, they describe how the hand moves relative to the treatment region. At a local scale, they describe contact posture, palm orientation, thumb articulation, finger coordination, and the sequencing of sub-actions within a manipulation. This distinction is clinically relevant because a technique such as kneading or thumb-rubbing may involve limited gross displacement while still containing highly structured local motion.

Dynamic descriptors characterize the time-varying mechanical dose applied to tissue. Relevant variables include mean force, peak force, force variability, impulse, loading rate, dominant frequency, duty cycle, waveform symmetry, and cycle-to-cycle regularity [23,24,31,32]. These parameters are often more clinically informative than visual appearance alone because they directly describe tissue exposure. Pressing techniques, for example, often exhibit sustained high-force plateaus with gradual release, whereas rolling and vibration depend on rhythmic regularity and spectral stability. Percussion or beating is better understood as a sequence of short-duration, impulse-dominant events. In translational terms, such dynamic signatures define what the robot must reproduce.

A rigorous extraction framework should therefore combine synchronized measurement of motion and force wherever possible. Common tools include motion capture systems, inertial sensors, instrumented gloves, six-axis force/torque sensors,

tri-axial tactile sensors, and pressure-mapping arrays [23,24,31,32]. The most informative studies further incorporate tissue-level measures such as ultrasound, elastography, electromyography, local hardness, or pain threshold, because the clinically relevant question is not only what the therapist did, but also what the tissue experienced.

To improve reproducibility, massage manipulation should be represented statistically as a structured set of measurable variables. The mean force can be defined as

$$\mu_F = \frac{1}{T} \int_0^T F(t) dt \quad (1)$$

the force standard deviation as

$$\sigma_F = \sqrt{\frac{1}{T} \int_0^T (F(t) - \mu_F)^2 dt} \quad (2)$$

the impulse as

$$J = \int_0^T F(t) dt \quad (3)$$

the dominant frequency as

$$f_c = \arg \max |\mathcal{F}\{F(t)\}| \quad (4)$$

and the coefficient of variation as

$$CV = \frac{\sigma_F}{\mu_F} \times 100\% \quad (5)$$

These parameters define massage in terms that are comparable across therapists, sessions, patient groups, and robotic platforms.

Table 2. Recommended quantitative descriptors for massage manipulation analysis.

Domain	Variable	Symbol / expression	Clinical relevance	Robotic relevance
Position	Displacement	$s(t)$	Reflects treatment coverage and local targeting	Defines spatial trajectory reproduction
Velocity	Mean / peak velocity	$\bar{v}, v_{\max}$	Influences tempo and comfort	Affects rhythm fidelity
Acceleration	Peak acceleration	$a_{\max}$	Related to abruptness of stimulation	Important for impact-like maneuvers
Force amplitude	Mean force	$\mu_F = \frac{1}{T} \int_0^T F(t) dt$	Represents overall loading dose	Basic force target
Force dispersion	Standard deviation	σ_F	Reflects variability and stability	Indicates consistency of control
Peak load	Maximum force	$F_{\max}$	Relevant to tolerance and safety	Critical safety threshold
Impulse	Time-integrated force	$J = \int_0^T F(t) dt$	Reflects cumulative exposure	Useful for dose comparison
Rhythm	Dominant frequency	$f_c = \arg \max \mathcal{F}\{F(t)\} $	Important for rolling, vibration, percussion	Measures frequency fidelity

Temporal stability	Coefficient of variation	$CV = \frac{\sigma}{\mu}$	Reflects regularity	Evaluates repeatability
Agreement	Intraclass correlation	ICC	Assesses reproducibility	Evaluates expert-robot consistency
Bias	Mean difference	$\bar{d}$	Detects systematic bias	Detects robot dose bias

As summarized in Table 2, quantitative extraction serves two linked purposes: clinically, it clarifies massage dose; technically, it provides the parameters required to map expert skill onto robot-executable control representations.

4. Robotic Reproduction of Massage Manipulations and Clinical Translation

Massage robotics has progressed from repetitive mechanotherapy devices toward increasingly adaptive systems that incorporate sensing, compliance, and learning. Early developments focused primarily on demonstrating feasibility [36,37]. Subsequent systems introduced anthropomorphic arms, elastic joints, force sensing, and dynamic control frameworks intended to emulate therapeutic contact more realistically [39,40,41,42]. More recent work has extended these capabilities to region-specific applications such as abdominal massage, oral rehabilitation, and physical therapy massage robots equipped with motion tracking and force-regulation strategies [51,52,53,58-64].

From a clinical perspective, the value of robotic massage depends less on visual anthropomorphism than on whether it can reproduce therapeutically meaningful mechanical patterns. At least three forms of fidelity are relevant. Mechanical fidelity refers to whether the target motion-force pattern is reproduced with acceptable error. Tissue-interaction fidelity refers to whether this pattern remains stable when applied to variable, deformable, patient-specific tissue. Clinical fidelity refers to whether the delivered manipulation generates outcomes relevant to treatment goals, such as pain relief, reduction in muscle hardness, improved function, or acceptable comfort. These domains are related but not interchangeable. A robot may track a trajectory accurately and still fail to deliver the intended biological stimulus if its contact behavior is poorly adapted.

This is why compliant control has become central to massage robotics. Massage is a contact-rich task performed on a living, deformable, and mechanically variable surface. Pure position control is often too rigid, because small geometric mismatch can generate large force errors. Pure force control may stabilize load but degrade trajectory shape, spatial coverage, or continuity of motion. In contrast, impedance control, admittance control, and hybrid force-position strategies allow the robot to regulate contact adaptively while preserving the essential structure of the manipulation [70-74]. Such approaches are especially important in clinical contexts, where safety, tolerance, and reproducibility are inseparable from technical performance.

Learning-based methods have further expanded the scope of robotic massage. Dynamic movement primitives, Gaussian mixture modeling, reinforcement learning, and learning from demonstration provide practical frameworks for encoding human performance into transferable control representations [65-69,75-78]. This is particularly relevant for massage because the task contains rich skilled variation that

is difficult to program explicitly through fixed trajectories alone. When expert demonstrations can be decomposed into interpretable motion-force primitives and executed under compliant control, robotic massage becomes a form of structured therapeutic reproduction rather than mere automation.

Clinical evidence remains limited but encouraging. A randomized controlled trial in nonspecific low back pain reported beneficial outcomes when robot-assisted massage was combined with standard care [44]. The oral rehabilitation robot series and related studies demonstrated that robotic massage of the masseter and temporal muscles can be implemented in a clinically meaningful way and evaluated through sonographic and outcome-based measures [58-64]. Other studies have examined head-care, relaxation response, and comparative effects of robotic versus manual massage in sports or wellness settings [45,56,57]. Although heterogeneous in methodology and sample size, this literature supports the feasibility of robot-assisted massage across more than one application domain.

Dual-arm massage is particularly relevant in this translational context. Many real manual therapies are inherently bimanual: one hand stabilizes or preloads tissue while the other delivers the principal action. This is common in the cervical region, lumbar paraspinals, abdominal wall, shoulder girdle, and temporomandibular area. A dual-arm robot may therefore be better positioned to reproduce clinically familiar strategies such as stabilize-and-treat, bilateral-symmetric treatment, preload-and-oscillate, or stretch-and-release. At the same time, dual-arm systems introduce additional challenges, including force sharing, coordination of two compliant contacts, collision avoidance, and more complex workspace coupling. Their translational value will depend on whether this added complexity yields superior mechanical and clinical performance.

5. Discussion

The literature reviewed here indicates that massage robotics is increasingly emerging as a translational field that links manual therapy, biomechanics, sensing, and adaptive control. However, several conceptual and methodological barriers continue to limit progress.

A central issue is that massage research still too often describes intervention content by name rather than by dose. In both manual therapy trials and robotic studies, manipulations are frequently identified as pressing, kneading, rolling, or vibration without adequate quantitative description of the delivered stimulus. This limits reproducibility and makes it difficult to determine whether two studies are evaluating comparable interventions. Robotics makes this problem especially visible: if the target behavior is not quantified, it cannot be encoded, reproduced, or validated in a rigorous way. The increasing use of motion capture, force sensing, and tissue-response assessment therefore has broader value, because it strengthens the scientific foundation of manual therapy itself.

A second issue concerns how expert-to-robot reproduction should be evaluated. Many studies report correlation coefficients or tracking error, but such metrics alone are insufficient to establish clinically acceptable replication. High correlation may coexist with systematic bias, whereas low average error may conceal instability across cycles or patients. When the question is whether robotic execution is acceptably close to expert performance, agreement metrics are particularly important. Intraclass

correlation coefficients, Bland–Altman analysis, and equivalence testing are generally more informative than simple null-hypothesis significance testing.

For Bland–Altman analysis, the mean difference and 95% limits of agreement may be written as

$$\bar{d} \pm 1.96 \times SD_d \quad (6)$$

and equivalence may be judged by whether the confidence interval of the observed difference lies within a predefined margin $[-\Delta, +\Delta]$. These methods are preferable when the practical objective is not merely to detect a difference, but to determine whether any difference is small enough to be clinically acceptable.

Table 3. Suggested statistical indices for expert-to-robot comparison.

Objective	Statistical method	Interpretation	Strength	Limitation
Linear similarity of waveforms	Pearson's r	Measures linear association between expert and robot time series	Easy to report and interpret	Insensitive to systematic bias
Monotonic similarity	Spearman's ρ	Measures rank-based association	Robust to non-normality	Does not assess absolute agreement
Time-series alignment	DTW distance	Measures similarity after temporal alignment	Useful for phase-shifted rhythmic signals	Less clinically intuitive
Reproducibility / agreement	ICC	Assesses absolute or relative agreement	More suitable than correlation alone	Depends on ICC model selection
Systematic bias	Bland-Altman analysis	Shows mean bias and limits of agreement	Clinically interpretable	Requires an acceptable range
Group difference	Paired t-test / Wilcoxon test	Tests statistical difference	Standard inferential method	No difference does not prove equivalence
Equivalence	TOST / equivalence margin	Tests whether difference lies within a predefined bound	Better for replication validation	Requires justified margin
Magnitude of difference	Cohen's d	Quantifies practical difference	Useful for effect interpretation	Sensitive to variance

A third issue is the persistent gap between engineering outcomes and clinical outcomes. Some robotic massage studies emphasize mechanism design, trajectory planning, or force stability, whereas clinical research is primarily concerned with pain relief, disability reduction, relaxation, comfort, and safety. These domains should not be separated. A robot that reproduces a waveform accurately but fails to produce clinically meaningful benefit cannot yet be considered therapeutically successful. Conversely, a clinical effect observed without a clearly defined and reproducible dose is difficult to interpret or optimize. Future studies should therefore evaluate mechanical fidelity, tissue-interaction fidelity, clinical fidelity, and safety within a unified translational framework.

Table 4. *Translational evaluation framework for massage robotics.*

Evaluation level	Engineering indicators	Clinical indicators	Example interpretation
Mechanical fidelity	Trajectory error, force error, frequency error, impulse error	—	Whether the robot reproduces the intended motion-force pattern
Tissue-interaction fidelity	Pressure distribution, normal-shear ratio, contact stability, slip rate	Pain during treatment, tolerance, localized discomfort	Whether the robot interacts with tissue safely and plausibly
Clinical fidelity	—	Pain intensity, ROM, disability score, muscle hardness, relaxation, patient satisfaction	Whether the reproduced manipulation leads to meaningful therapeutic response
Safety fidelity	Peak force limit, loading rate, emergency stop response	Adverse events, post-treatment soreness, intolerance	Whether the intervention remains within acceptable risk bounds

Table 4 also highlights why tissue-interaction fidelity may become a decisive concept in future research. The same robot output can produce different biological stimuli depending on tissue stiffness, contour, friction, guarding, or pain sensitivity. Patient-specific adaptation is therefore not an optional refinement but a central requirement. At present, many systems remain feasibility-oriented and do not yet fully address these factors.

Dual-arm systems warrant special attention within this discussion. Their main significance lies not in technological complexity alone, but in their closer resemblance to the cooperative logic of human hands. In many therapeutic situations, one hand stabilizes, tensions, or protects while the other manipulates. This coordination may improve dose distribution, reduce local peak loading, and better reflect expert clinical practice. However, dual-arm control is substantially more demanding because it requires coordinated compliant contact, force sharing, and safety management across two end effectors. The clinical value of dual-arm massage robotics will therefore depend on whether it can demonstrate meaningful advantages over simpler systems in both mechanical and therapeutic terms.

Overall, the field is progressing in a promising direction, but it remains immature. The most important priorities for future work include better quantitative dose definition, stronger linkage between extraction and execution, disease-specific clinical validation, multimodal tissue sensing, and patient-adaptive compliant control. The long-term contribution of massage robotics may lie less in replacing therapists than in transforming manual therapy into a more measurable, auditable, and experimentally testable intervention.

6. Conclusions

Massage manipulation can be understood as a structured mechanical intervention delivered to a nonlinear biological substrate. From this perspective, extraction of expert massage skill requires synchronized characterization of motion, force, rhythm, and tissue interaction rather than reliance on qualitative labels alone. Robotic systems have already demonstrated the feasibility of reproducing massage-related patterns in applications such as low back pain treatment, oral rehabilitation, and wellness-oriented care. However, the field remains constrained by incomplete dose reporting,

limited clinical evidence, and insufficient integration of engineering performance with therapeutic outcomes.

A clinically meaningful roadmap for massage robotics should prioritize quantitative dose definition, interpretable kinematic and dynamic descriptors, safety-aware compliant control, individualized tissue adaptation, and disease-specific validation. Within this framework, dual-arm systems merit particular attention because they more closely reflect the bimanual logic of expert manual therapy and may offer a stronger bridge between therapist expertise and reproducible robotic care. The future of the field lies less in simple automation than in the development of standardized, adaptive, and clinically accountable mechanical therapy.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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