Robotica (2005) volume 23, pp. 277–282. © 2005 Cambridge University Press
doi:10.1017/S0263574704001298 Printed in the United Kingdom

# Residual kinetic imaging: a versatile interface for prosthetic control

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## SUMMARY
We studied the pressure patterns in the residual limbs of trans-radial amputees during their voluntary commands for finger taps. Topographic maps of pressures exerted against the hard prosthetic socket were registered with an array of 32 pressure sensors, to produce residual kinetic images (RKIs) of the limb. Results with 2 untrained subjects demonstrated that RKIs are reliable decoders of efferent commands. Coupled with a trained filter, RKIs can provide biomimetic control over multiple degrees of freedom.

KEYWORDS: Controller; Prosthetic; Upper-limb; Dexterity.

## I. INTRODUCTION

### *I.1. Rationale*
While robotic technology has produced hands that move with dexterity in many degrees of freedom (DOF),[1–7] controlling them is currently beyond the reach of human amputees. Prosthetic technology currently provides only grasping and wrist rotation, controlled by the user through learned, generally unnatural movements of his residuum. Thus, despite steady advances in basic prosthetic functioning through improved processing of multiple myoelectric signals,[7] human control remains the biggest challenge to restoring dexterity.

The need for more dexterous hand prostheses is underscored by recent surveys of experienced users of advanced (trans-radial) prostheses.[8,9] The survey revealed that the most important functions not presently available to them were ability to type and use a word processor, and ability to bend fingers. These inadequacies of current technology may explain the large percentage (up to half) of upper limb amputees who use no functional prosthesis on a regular basis.[8–10] Thus new approaches are required to provide greater restoration of hand function.

The present study addresses the human/machine interface; other components of upper-limb prostheses, including socket materials, linkages, sensors, microprocessors, power sources, actuators, and multi-functional hands, while not yet optimized, are already well developed.[11] Several laboratories have produced robotic hands that can almost replicate the dexterity of the human hand, having up to 22 DOF.[12,13] While not all these are suitable as prosthetic devices due to weight and power requirements, some appropriate multi-finger hands have been prototyped using general purpose actuators as well as advanced actuators being developed specifically for prosthetic applications.[4,11–17]

### *I.2. Biomimetic Control*
Biomimetic devices function through mimicking natural processes in biology. Hence, A biomimetic controller would allow the user to control his hand movements naturally using his original motor pathways. Success of the biomimetic approach requires: (i) that the potential user has retained his relevant central motor functions, along with an ability to physically express them in accessible parts of his residual anatomy and (ii) that these central commands or volitions are decipherable. The first requirement is at least partially satisfied since studies have shown that many amputees, and some of those with congenital limb deficits, who sense a phantom limb, can also manipulate it.[14,15,18]

Requirement (ii) above is as yet far from satisfied, due to the complexity of the human motor system. First, most human movements, especially those of the hand, are directed by neural circuits arranged in both open-and closed feedback loops, operating at central and peripheral levels.[19] Voluntary movements originating at the highest level of the motor cortex, are shaped by feedback from intermediate centers, such as the cerebellum, and peripheral feedback from tactile, proprioceptive, and visual modalities.

Secondly, even the simplest and most open-loop of motions such as finger tapping are difficult to decipher for kinematic purposes; each finger is controlled by several muscles acting both directly and reciprocally, which are each controlled by even more numerous nerve fibers. Direct recording and decoding of multiple motor neuron signals to derive kinematic information is not yet practical. Myoelectric signals are simpler and more readily accessible, but their indirect and often unpredictable relationship to joint motions limits their utility for decoding multi-DOF volitions.[20] Thus new approaches to deciphering commands at the periphery are required.

Little is known of the functional capacity of muscles in the residuum. There are wide variations in the patho-anatomy of traumatic amputations among amputees, in terms of length of residuum, type and age of injury, and tissue/muscular health.

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Table I: Clinical Characteristics of Subjects.

| Subject | Age | Age of Amputation | Level and cause of Amputation | Tissue Condition |
|---|---|---|---|---|
| A | 27 | 12 | Trans Radial, Upper third, electrical burn | Soft, scarred, fatty |
| B | 69 | 33 | Trans Radial, Distal third, sharp trauma | Firm, unscarred, Lean |

Most amputations occurring below the elbow retain at least portions of muscles that flex and extend their metacarpal-phalangeal joints. These extrinsic muscles insert at the elbow and end in tendons beginning in the distal third of the forearm and are responsible for up to half the control over the flexion/extension forces exerted by the finger tips. In addition to those muscles directly operating finger joints, several other muscles within the forearm are active, or at least passively moved, during certain finger movements. These include wrist extensors and flexors that contribute to such motions as pinching, grasping, and tapping, and are generally deep. Thus, most finger movements involve many diverse muscles throughout the residuum. Restoring biomimetic control therefore requires a system that registers the maximum amount of kinetic activity within the residuum.

A versatile controller for externally powered prosthetic hands would decode central trajectory and velocity commands for each finger, and translate them into finger joint angles and speeds, operating much like a computer of inverse kinematics. Such a controller, by tapping in to natural motor pathways, could restore more natural dexterity to amputees. Herein we present a controller that operates by extracting force patterns exerted at the surface of the entire residual forearm, i.e., the residual kinetic image (RKI). Our preliminary tests involve simple finger taps, since they are primarily pre-programmed motions and require little or no feedback from the finger joints themselves.[21,22]

## II. METHODS

### *II.1. Human subjects*

Subjects were tested following informed written consent, after approval from the Rutgers University Institutional Review Board. An initial screening exam was performed by questionnaire and by direct palpation of the forearm during requested finger motions. Criteria for acceptance into the study were (i) a trans-radial amputation, (ii) the presence of afferent and efferent phantom activity, (iii) palpable soft tissue movement in the limb and (iv) no reported discomfort during testing. The accepted subjects were both male, of average body build and weight, having traumatic amputations with the characteristics listed in Table I.

### *II.2. Sensors and preliminary screening*

The primary sensor interface contained a grid of 32 myo-pneumatic (M-P) sensors embedded in a silicone sleeve custom molded to the residuum (Figure 1). Alternatively, 8 sensors were incorporated into a linear array on a bracelet. To record pressures, these arrays were wrapped tightly around the residuum and interposed between it and a standard hard plastic socket. M-P sensors were fabricated from open-cell foam encased in a plastic film, as previously described.[14] Anatomical location of sensors in reference to distal end and circumferential position were recorded prior to testing. The bracelet recorded a series of limb segments starting from the most distal, and moving stepwise proximal in 4 cm increments. The sleeve could record all 32 sites without repositioning.

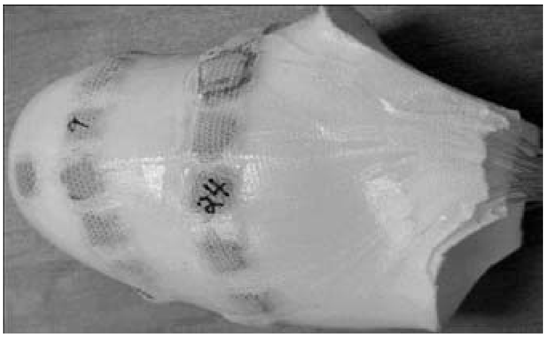

Fig. 1. A *Smart-Sleeve*. The final product is a custom-formed silicone sleeve with sensors (black squares) embedded inside in predetermined locations. Sensor hoses exit the sleeve at right. Total Length from the distal end to the olecrenon posteriorly, and to the fold of the elbow anteriorly, for subject A ∼ 15 cm, for Subject B ∼ 23 cm.

Placement of sensors in the sleeve was determined in a quasi-custom manner by preliminary testing with palpation and manually placed sensors. The average circumferential spacing was about 2 cm. The sleeve was made with silicone gel and catalyst (Otto Bock, Germany Patents 617H43 and 623T13) that were applied to the mold with attached sensors and allowed to set over several minutes.

### *II.3. Recording and data analysis*

Each M-P sensor was connected via tubing to a pressure transducer (Sensym SCX-01, Santa Clara, CA.), and connected to an 8-channel data acquisition board (DAP/1200, Microstar Laboratories, Inc., Bellevue, WA). Data from the M-P sensors were anti-alias filtered and sampled at 200 Hz per channel with 12-bit resolution, and stored to files for offline processing. CPU was a 386-PC operating at 66 MHz. Arrays of sensors were evenly spaced about the residual limb. Brief tapping motions produced generally monophasic pressure pulses at distributed regions of the residuum, as described previously.[14] Pressure data were initially analyzed using DADISP (Newton, MA); peak pressures during tapping were squared and were subsequently processed into maps using MathCAD (Mathsoft, Cambridge, MA). Statistical analyses, including variance and correlation coefficients, were computed in Microsoft Excel.

### *II.4. Imaging of residuum*

Magnetic resonance imaging was performed on the limb of one subject for an internal view of the amputated muscles and associated structures. A longitudinal cross section was

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taken, followed by 32 transverse slices. Imaging was done at the Laurie Imaging Center of the Robert Wood Johnson Medical Center (New Brunswick, NJ). Standard photography was also done.

### *II.5. Protocol*

Subjects were prompted to move each finger twice in sequence until all of their phantom fingers (3 to 5 depending on the subject) were moved. Data were recorded from either the smart sleeve or from the bracelet moved sequentially up the residuum. Sensor coordinates were established with respect to the distal-proximal axis (limb axis) and normalized circumferential positions, while subjects held their residuum in a neutral position. It should be noted that 'standard anatomical position' does not directly apply to an amputee. With this consideration, coordinates were as follows: The abscissa is the longitudinal distance from the distal end, the ordinate is a radial measurement starting from the most lateral point and moving anteriorly in a circle. The most lateral point was located both at 0 and 1, and the anterior midline, medial, and posterior midline are represented by 0.25, 0.5 the medial, and 0.75, respectively. An iso-bar contour map was then produced, showing areas of pressure corresponding to specific finger volitions.

Following RKIs, subjects were tested for their ability to control a virtual hand, with 5 moveable fingers. Algorithms for decoding modified versions of RKIs were applied as previously reported.[23]

## III. RESULTS

### *III.1. Residual kinetic imaging*

Both subjects reported the ability to sense and move specific phantom fingers upon request and did not report discomfort during testing for up to one hour. Peak regional pressures of approximately 3 kPa were recorded from both subjects. RKIs for taps of 3 phantom fingers are shown for subject A in Figure 2. The maps revealed clearly delineated regions of high and low pressure during each finger motion. Each finger movement caused a distinctive map, indicating the discriminability of finger volitions based on distributed socket pressures. High-pressure areas occurred at the distal anterior surface of the residuum for the thumb volition, for the middle finger at the medial surfaces, both proximally and distally, for the pinky at the medial surface proximally. In repeated tests, subject A produced RKIs that were nearly identical to those shown here. Subject B produced RKIs for all 5 fingers (not shown) that were similarly discriminable amongst the fingers, but were not similar to those of subject A. Reproducibility of RKIs in repeated tests over several weeks was demonstrated by use of a pattern recognition algorithm.[23] These studies showed that, after a few minutes of training, subjects were able to control fingers independently, using their phantom limb motor commands.

In order to estimate the degree of spatial resolution required for RKI discriminability, we examined variability and correlation coefficients among sensors. Those sensors recording the highest variability during different motions and the lowest correlations with other sensors represent the most significant in terms of information transfer. Groups of sensors with high variability and high correlation coefficients are probably measuring pressure from common origin and may be redundant. Figure 3 shows a relatively wide range of pressures recorded among the various sensors. Sensors recording no pressure changes may possibly be superfluous. Correlation coefficients of all sensors with variability > 0.1 were examined and are shown in Figure 4. Groups of highly correlated sensors are highlighted since each group is likely

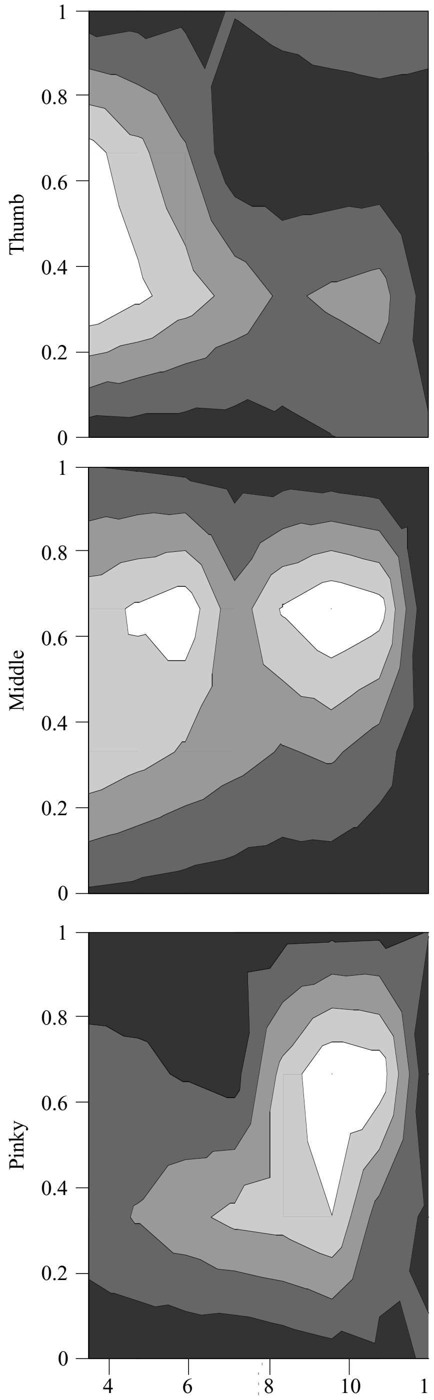


Fig. 2. RKI of residual limb movements for subject A during requested finger tapping. Each requested movement is identified by a unique image of pressure energies. Maximum pressures were approximately 3 kPa with white being the greatest and black being no change.

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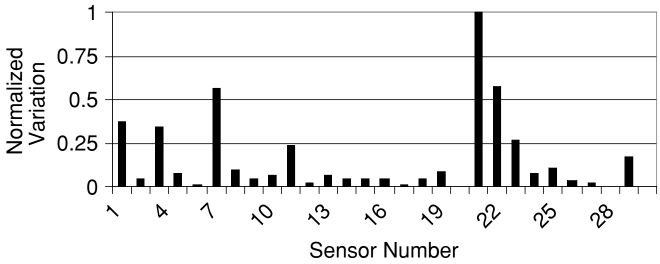


Fig. 3. Variation of amplitude of peak pressure during requested volitional commands for subject A. Sensor 21 had the highest variability, and the others were normalized to it.

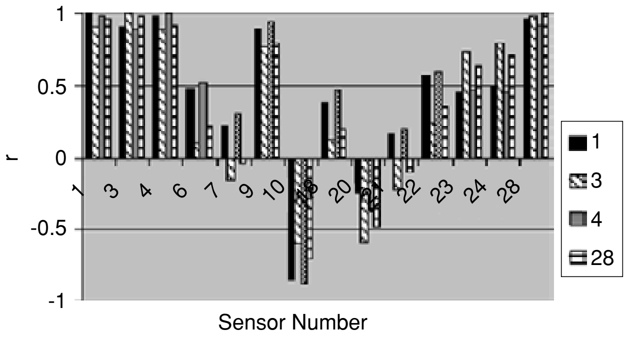


Fig. 4. Correlation Coefficients for selected sensors for subject A. Highly positive correlation coefficients represent sensors picking up the same information describing one volitional command. Highly negative correlation coefficients are equally significant for discriminability.

to represent a single volitional command. These results suggest that a sleeve could be made with substantially fewer sensors, if placement were carefully chosen. If the placement precision requirement is not desired, then a fuller array would be more appropriate.

*III.2. Residual anatomy*

Surface morphology and internal structures of the residuum of subject A were examined in photographs and MRI slices in order to observe correspondences between his anatomical and functional images (Figures 2 and 5). As expected from his surface morphology and tissue compliance (scarred and fatty), his residual muscles are nearly surrounded by a large layer of mostly fat, with scar tissue as well (Figure 5). The images revealed bone and muscle locations, but no tendons, probably because the level of amputation was above that of the forearm tendons. The only superficial muscles are located in a small region near the distal-medial aspect (Figure 5 A and B). The volume ratio of fat and scar tissue to muscle is approximately 1:1, much higher than the normal whole body average of roughly 15% body fat. Although muscle structure can be identified, no obvious features corresponded with areas of high pressure activity. Note that the highest activities for two of the fingers (pinky and middle) were found in the medial area, where the fat layer is minimal. Discs superimposed on the image denote areas of observed movement.

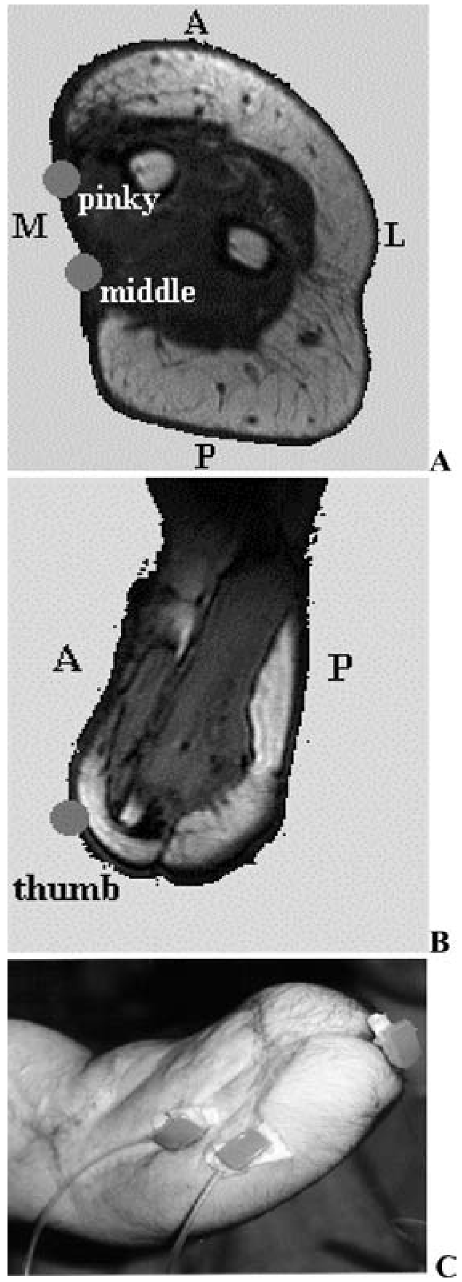


Fig. 5. MRI photographic images and of subject one's residual limb. Panel A shows a transverse slice near the distal end. Panel B is a longitudinal slice. Areas of movement have been superimposed as discs on the image. 5C is a photograph of Subject A's residual limb for comparison. M-P sensors are attached at three sites.

*III.3. Prosthetic control*

The RKIs indicated the likelihood of adequate control over at least 3 prosthetic fingers. This possibility was tested by asking the subjects to move fingers on a virtual hand presented to them on a computer screen. Using our discrimination algorithms previously published;[23] both subjects readily gained reliable control over 3 fingers.

## IV. DISCUSSION

*IV.1. Limitations and validity of the study*

This preliminary study reports on a novel method for deciphering volitional commands from trans-radial amputees.

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Results are encouraging, since neither subject was an ideal candidate: subject A has a short residuum, highly scarred from the electrical injury, and atrophic muscles; subject B had been amputated over 30 years prior. The MRI images, in conjunction with the RKIs, confirm the ability of the residuum to generate significant, spatially distributed pressures at the surface, despite large amount of fatty and scar tissue. Further optimization of sensing techniques will no doubt improve the efficiency, and reliability of decoding volition.

The ability of RKIs to encode features such as proportional force control is unknown. We made no attempt to estimate the amount of intended force that was commanded by the subject, and therefore cannot predict the degree of proportional control possible. Previous studies have shown that in the absence of proprioceptive feedback from finger motions, developing dexterity and coordination is a relatively slow process. Our preliminary results support the importance of direct, as opposed to virtual, proprioceptive feedback, since physical control of fingers, provided by a multi-finger mechanical hand, seemed to promote the acquisition of dexterity.[23,24]

Pressure variations due to external loading have not been a problem under controlled laboratory conditions, however could interfere in everyday use. Pressures due to external forces could be accommodated with appropriate filtering because spatial patterns for external loads should be different from internal pressure changes.

After trans-radial amputation, finger muscles perform no work, a deficit that usually causes atrophy of the muscles, along with associated peripheral nerves and tendons.[8] Motor control is also severely affected, probably similar to that seen in neurologically different patients[22] since residua are anatomically deafferented. Nevertheless, many amputees retain functional control over their residual muscles, as shown by non-invasive magnetic recordings,[21] as well as by our previous studies.[15] Subject A had extensive scarring and pronounced muscle atrophy, as shown by his MRI, yet he produced distinct and reproducible RKIs. Central circuitry for finger motions was clearly functional in both subjects, in agreement with fMRI measurements of motor cortex made during phantom limb imaginary movements of amputees.[21] It is therefore likely that many trans-radial amputees would be able to express control over finger movements through activity in their residual limbs, as confirmed by our small sample in the present results, and by previous studies.

### *IV.2. Comparison with EMG methods*

EMGs are not ideal signals for controlling multi-DOF volitions. First, flexion/extension of each metacarpal-phalangeal joint involves coordination among a set of several extrinsic muscles, operating as reciprocal pairs, situated both deeply and superficially in the forearm. EMG recordings obtained from all 3 extrinsic muscles for each joint could possibly be related to volitional trajectories, but sensing the multiple EMGs would depend critically on precise site selections. This is a formidable task, since non-invasive electrodes are not adequately specific, and trans-cutaneous electrodes are not generally tolerable. Secondly, decoding spatially distributed EMG signals requires considerable processing, including extraction of a pattern from each site, followed by extracting coupled patterns from several sites. Pattern extraction is necessary since EMG signals are asynchronous electrical pulses from many muscle fibers, transmitted through variable tissue and skin, and hence in their raw state resemble noise. Finally, EMG signals can be degraded by electrical interference that may arise externally or from actuators on the prosthesis, and by sweat due to effort and heat in the socket.

In contrast to EMGs, the RKI neither selects nor depends on identifiable muscular action, but rather represents volitions by the entire 3-D pattern of forces in the residuum. RKI patterns can be discriminated using filters that can be readily trained and re-trained as needed. This paradigm therefore lessens the precision requirement of sensor placement, an important practical consideration for amputees whose residuum is constantly changing, and who must don and doff their prosthesis daily.

## V. CONCLUSION

Both test subjects produced distinct pressure patterns on the surface of their residual limbs during their volitions for finger flexion/extension. We represented these patterns as residual kinetic images (RKIs) associated with specific finger motion requests and decoded RKIs with a trained filter to restore volitional control of finger motions.

**Acknowledgements**

Support was provided by funds from NIH Biotechnology Training Program, Grant # T32 GM08339, Rutgers University Strategic Opportunity Award, and an NIH STTR grant to Nian-Crae, Inc.

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