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HUMAN AND ROBOT FINGER KINEMATIC ANALYSIS USING WAVELET THEORY

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Abstract: *In this paper we analyze the kinematics of the human finger joints versus an anthropomorphic robotic finger using wavelet theory. As such, we propose an approach to evaluate the kinematics of both human and a robotic finger joins by using the decomposition of the signal and comparing the detail energy levels. The results show that the detail energy of the signal corresponding to level 5 for robot finger is much lower than the similar energy of human joint finger.*
Key words: *human finger, robot finger, kinematics, wavelets, Biometrics, goniometer*

1. INTRODUCTION

The human hand is one of the most complex tools from the anatomical and biomechanical perspectives. The human hand plays a very important role in the life of an individual by:

- helping the human being while eating or procuring aliments;
- maintaining personal hygiene;
- ensuring all the actions required for producing goods;
- key tool in the non-verbal communication process with other individuals by sign gestures made with human hand and/or fingers, many times more important than the verbal communication;
- ensuring the non-verbal communication by writing, drawing, painting, music etc;
- gathering sensorial information from the outside environment (tactile, temperature, pressure etc.) through the fingers and hand skin. As one could observe, the human hand surpasses any other tool in terms of functionality, thus enriching the life in so many ways.

From the anatomical perspective, the human hand is a system which consists of multi-degrees of freedom anatomical joints which helps to produce the human movements of the phalanxes, fingers, palm and/or the entire upper hand. In doing so, each finger could be associated with 4 degrees of freedom mechanical structure (the index, middle, ring and little fingers), except the thumb finger which has 3 degrees of freedom. Moreover, two degrees of freedom anatomical joint (the hand-forearm joint) enable the motions of flexion-extension and abduction-adduction of the entire human hand with respect to the forearm, as one could observe from Figure 1.

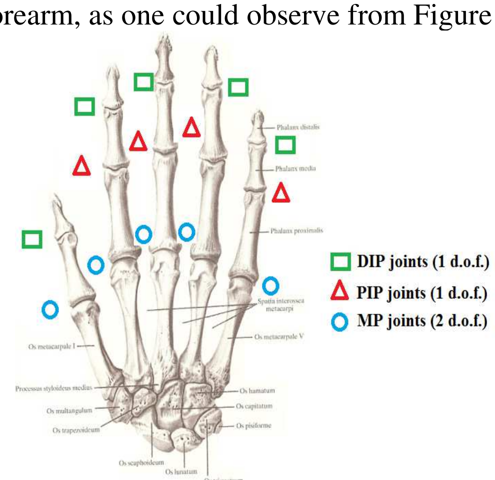

Fig. 1. The human hand skeleton (DIP- distal interphalanx joints, PIP- proximal interphalanx joints, and MP- metacarpal joints [1])

The human hand skeleton has 8 carpal, 5 metacarpal and 14 finger bones, which form 12 intercarpal joints, 8 joints formed between carpal and metacarpal bones, 4 joints between metacarpals, 5 joints (2 D.O.F.) formed between

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metacarpal and finger bones (phalanxes) – MP joints, and 9 joints (1 D.O.F.) between phalanxes – PIP and DIP joints, as shown in Fig. 1. Therefore, in total the human hand skeleton comprises 27 bones and 38 joints from which 19 D.O.F only at the phalanxes level.

The kinematics of human and/or robotic finger joins was analyzed previously using various methods. For example, in paper [2] the kinematics of finger and human upper arm is studied using a motion capture system, while in [3, 4] the design and the robotic joints of an anthropomorphic hand-arm system are analyzed using chaos theory. The kinematic and dynamic analysis of the index finger has been performed employing the Runge-Kutta method by Zhifei, J. et al. in [5].

Our approach is to collect data regarding the human finger joints and a robot finger using a goniometer data acquisition system and to analyze each signal using wavelet theory. The aforementioned theory was first developed by the work of Daubechies [6] and Mallat [7] and used in various fields (economics, mechatronics, biomechanics, medicine etc.) to analyze certain signals of interest. For example, William, L. et al. [8] have used different wavelet families (Daubechies and Meyer) to analyze individual M-waves, signals collected from forearm muscles using surface EMG stimulation of patients with complete spinal cord injuries. Wavelets are used to remove noise and artefacts for the EMG signals collected from the arm muscles like biceps brachii and triceps brachii by Gradolewski, D., et al. [9]. Muscle fatigue occurrence is studied with the aid of wavelet transform in paper [10]. A method of recognizing human finger motion using Wavelet Transform of surface EMG signals collected from the arm is proposed by authors in paper [11]. Moreover, in paper [12], Boostani, R. et. al propose the evaluation of the 19 forearm EMG signal features for the control of a prosthetic hand employing wavelet theory. Wavelet decomposition of the signal and computation of energy for each signal in case of healthy human volunteers carrying asymmetric loads, from 0-12.5 kg in 2.2 kg increments, is carried out by Berceanu C. et al. in [13].

2. DATA COLLECTION AND PROCESSING

The experimental data was acquired in the Laboratory of Biomechanics from the INCESA – Center of Advanced Research of the University of Craiova.

The human middle finger flexion-extension motion (see Fig. 2) was recorded for four volunteers (one male and three females), with mean age of 34.5 (SD = 10.84), height (m) 1.78 (SD = 0.049), and weight (kg) 68.7 (SD = 10.21), having no pain symptoms and a robotic finger. The details of the human volunteers are depicted in Table 1. The anthropometric data for the volunteer's fingers are given in Table 2.

Table 1

The human subjects which participated to the study

Subject	Age	Sex	Height [m]	Weight [kg]
1	27	F	1.81	68
2	27	M	1.83	83
3	34	F	1.72	59
4	50	F	1.76	65

Table 2

Middle finger phalanx lengths

Subject	Proximal [mm]	Medial [mm]	Distal [mm]
1	32	23	25
2	32	24	25
3	34	26	27
4	30	25	27
Avg. [mm] **(SD)**	32 (1.63)	24.5 (1.29)	26 (1.15)
Robot	28	22	26

The data was collected using Biometrics Ltd. data acquisition system [14-20], employing a F35 sensor (goniometer) placed on the middle finger, as shown in Fig. 2.

3. RESULTS

Fig.3 shows the PIP joint law for a human subject with two signals, i.e. the raw signal and filtered (noise removed) signal. The clean signal was obtained using MATLAB software, with the aid of Daubechies's function of first order (db1 type).

Fig. 2. The goniometer placed on the finger used for data acquisition [14]

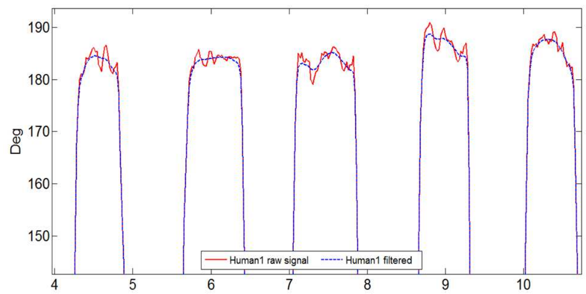

Fig. 3. The raw and filtered human finger signal for PIP joint

Moreover, in Fig. 4 one can observe a comparison between filtered PIP and MP motion signals for the four human subjects vs. the same robotic finger motion.

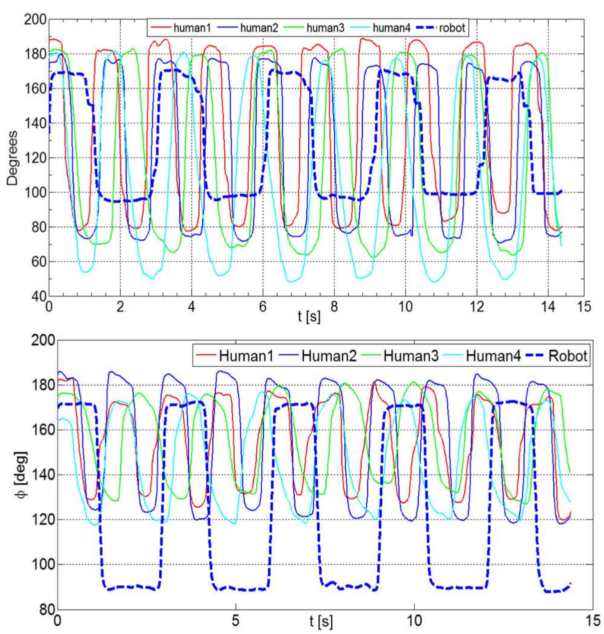

Fig. 4. The displacement for PIP and MP joints, for all five signals

One important tool to characterize the periodicity or instability of the motion is the Poincaré map. If the points are scattered on the map as motion evolves in time one can conclude that the motion is highly instable, the case of the human finger motion, see Fig. 5 a). By contrast, if the points accumulate on the map (forming a nucleus) one can say that the motion is much stable or periodical, the case of robotic finger motion, shown in Fig. 5 b).

We have done such an analysis with the MP joint motion for both human and robotic finger. In Figure 5 is presented the Poincaré map for human subject no. 3 vs. robotic finger. We can observe a similar pattern for all the subjects regarding the MP joint. Moreover, Poincaré map presents similar results for PIP joint, all the human volunteers. In Figure 6 we present the phase plane plots for the PIP joint both for human, Fig. 6 a), and robotic finger, as shown in Fig. 6 b).

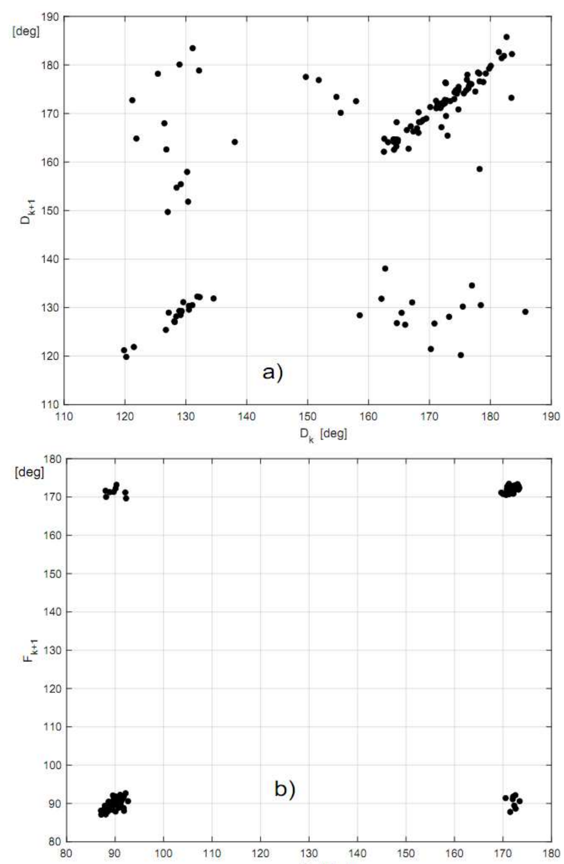

Fig. 5. The Return map of the maxima for MP joint, human a) vs. robot b)

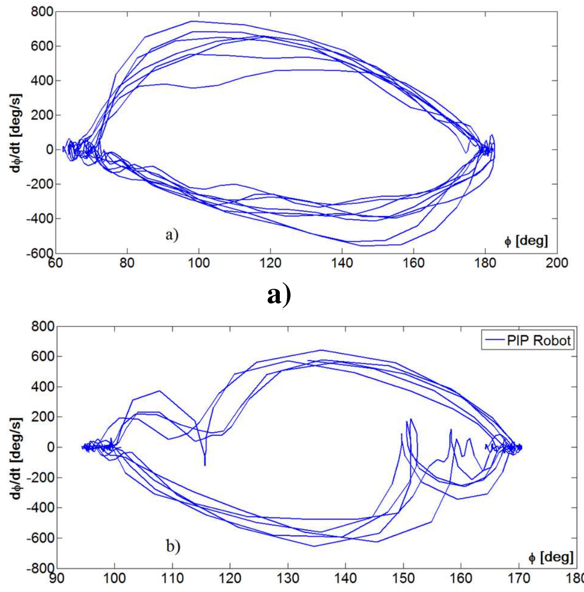

Fig. 6. The phase plane for PIP joint, human (a) vs. robot (b)

In order to assess other differences in the finger joints signals of human vs. robot, we have conceived a MATLAB algorithm, which decomposes the original signal into approximation, and detail functions (five levels, see Fig. 7 and 8). The analyzed signals are decomposed using Daubechies's wavelet functions, db8 type.

For discrete signals (countable in time domain), like PIP joint, the Discrete Wavelet Transform (DWT) will decompose the signal in a series of approximation (smoothing) and detail functions. As such, the initial joint signal can be written like in equation (1):

$$S = A_R[n] + \sum_{i=1}^{R} D_i[n] \tag{1}$$

The approximation and detail energy for each decomposition level are computed using the equations (2), while the full energy of the signal can be computed with eqn. (3):

$$\begin{cases} E_{A_R} = \sum_{j=1}^{N} \left| A_{R_j} \right|^2 \\ E_{D_i} = \sum_{j=1}^{N} \left| D_{ij} \right|^2 \end{cases} \tag{2}$$

$$E_{signal} = E_{A_R} + \sum_{j=1}^{N} E_{Di} \tag{3}$$

It must be noted that in eqns. (1), (2), and (3), R=5 is the level of signal decomposition; $A_R[n]$ is the approximation function, obtained by applying a low-pass filter and down sampling from the initial joint signal, as shown in Fig. 7; $D_i[n]$ are the detail functions, obtained by applying a high-pass filter and downsampling; $n=720$ is the number of samples for the signal. N is the number of detail and approximation coefficients at each decomposition level.

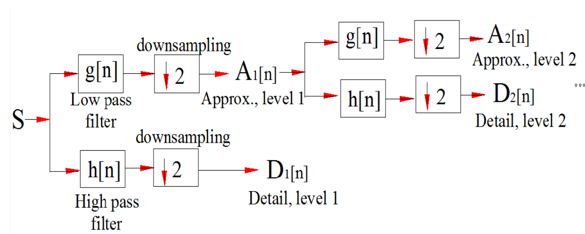

Fig. 7. The signal decomposition technique using wavelet transform, S is initial joint signal

The detail energy for all the five levels is shown and compared in Fig. 9. As one could observe from this figure, the detail energy for level 5 is significantly smaller for robot finger joint signal vs. human finger joint signal.

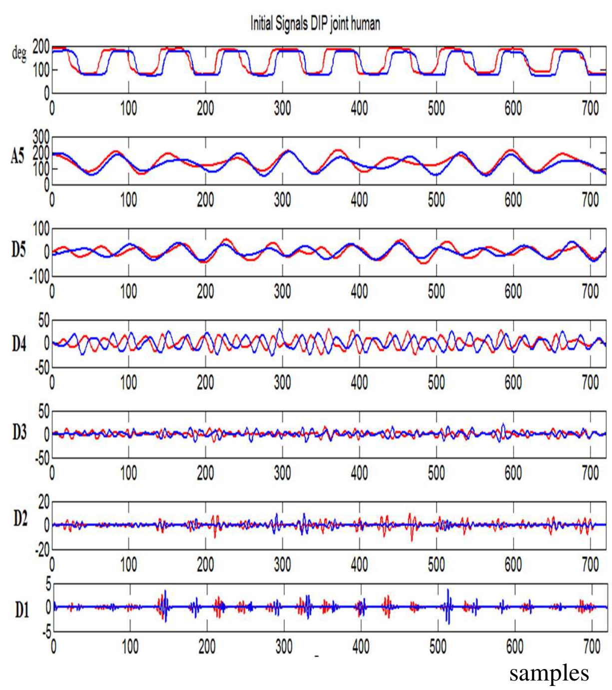

Fig. 8. The decomposition of the signal in approximation and detail functions for PIP joint human subjects

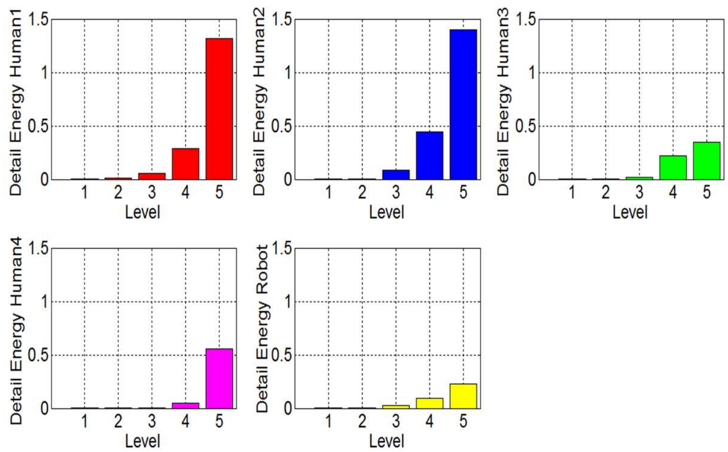

Fig. 9. Comparison between the detail energies of human vs. robot finger motion, PIP joint (five levels of decomposition)

4. CONCLUSIONS

In this paper we have analyzed, using wavelet decomposition technique, some signals acquired from the human finger motion of healthy individuals and compared these with the same motion of a robotic anthropomorphic finger. We have found that the detail energy for level 5, corresponding to PIP joint, is significantly smaller for robotic finger vs. human fingers motion, as shown in Fig. 9 and Fig. 10.

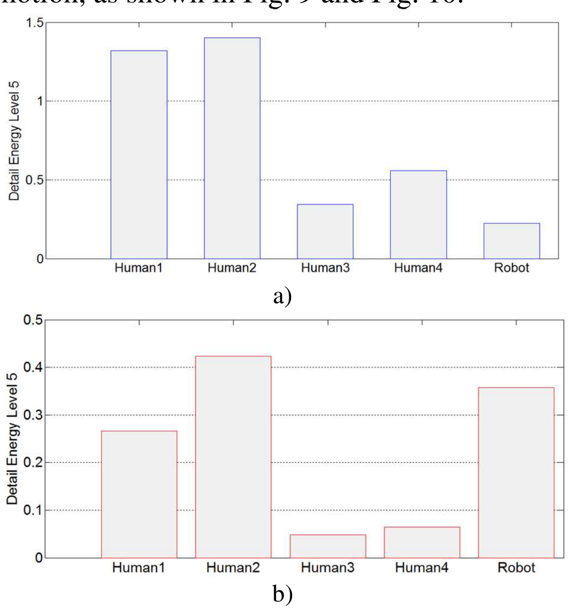

Fig. 10. The signal detail energies corresponding to the 5^{th} decomposition level human vs. robot PIP joint (a) and MP joint (b)

This is explainable due to periodic nature of the motion of the robotic finger. In the case of human finger motion, after some time and motion cycles, muscle and ligament fatigue come in place, thereby affecting the repeatability of the motion (both in amplitude and cadence).

An interesting continuation of this study will be to include human subjects with some impaired motion control (arthritis, for example) and compare the motion, from the energy level perspective, with the healthy subjects' motion. Furthermore, we propose the algorithm developed in MATLAB as a method to quantify the differences between kinematic stability of the movements of a healthy subject and a patient affected by diseases of the upper limb joints.

5. REFERENCES

[1] Sinelnikov, R.D., *Atlas de Anatomia Huma na*, MIR Publishing House, Moscow, 1975

[2] Berceanu, C., et al., *About an experimental approach used to determine the kinematics of the human finger*, Journal of the Solid State Phenomena, Robotics and Automation Systems, Vol. 166-167, pp. 45-50, 2010

[3] Berceanu, C., Tarniţă, D., *Mechanical design and control issues of a dexterous robotic hand*. Advanced Materials Research, 463, pp.1268-1271, 2012.

[4] Tarnita, D., Marghitu, D., *Analysis of a hand arm system*, Robotics and Computer-Integrated Manufacturing, 29(6), pp. 493-501, 2013.

[5] Zhifei J. et al., *The Kinematic and Dynamic Analysis of a Bionic Manipulator*, J. Phys.: Conf. Ser. 1948, 012078, 2021.

[6] Daubechies, I., *Wavelets: A different way to look at subband coding*, In Proc. 1st NJIT Symposium on Wavelets, Subbands and Transforms, April 1990.

[7] Mallat, S., *Theory for multiresolution signal decomposition: The wavelet representation*. IEEE Trans. Pattern Anal. Mach. Intell., 11(7), pp. 674–693, 1989.

[8] William, L., et al., *A method based on wave-lets to analyse overlapped and dependant M-Waves*, Journal of Electromyo-graphy and Kinesiology, Vol 63, 102646, 2022

[9] Gradolewski, D., Tojza, P.M., Jaworski, J., Ambroziak, D., *Arm EMG Wavelet-Based Denoising System.* In: Mechatronics - Ideas for Industrial Application. Advances in Intellig Syst and Computing, Vol. 317, 2015. Springer, Cham.

[10] Kumar, D.K., et al., *Wavelet Analysis of Surface Electromyography to Determine Muscle Fatigue*, IEEE Transactions on Neural Systems and Rehabilit Eng 11(4), 400–406, 2003.

[11] Jiang M., Wang R., et al., *A Method of Recognizing Finger Motion Using Wavelet Transform of Surface EMG Signal*, In Proc IEEE Eng Med Biol. Soc. 2005, 2672-4.

[12] Boostani R., Moradi M.H., *Evaluation of the forearm EMG signal features for the control of a prosthetic hand*. Physiol Meas. 2003 May, 24(2):309-19. PMID: 12812417

[13] Tarnita, D., et al., Experimental Characterization of Human Walking on Stairs Applied to Humanoid Dynamics, Advances in Robot Design and Intelligent Control, RAAD16, Springer, 540, pp.293-301, 2017.

[14] Biometrics Ltd., Goniometer&Torsiometer Operating Manual, available at https://sportsciencesafety.wordpress.stir.ac.uk/files/2020/09/biometricsGoniometer_UserGuide.pdf

[15] Tarnita, D., Marghitu, D.B., *Nonlinear dynamics of normal and osteoarthritic human knee.* Proceedings of the Romanian Academy, *18*(4), pp.353-360, 2017

[16] Berceanu, C., Marghitu D.B., et al., *Gait Analysis Parameters of Healthy Human Subjects with Asymmetric Loads*, Computer Methods in Biomechanics and Biomedical Engineering, Vol. 19(8), pp. 855-863, 2015.

[17]Tarnita, D., Berceanu, C. Tarnita, C., *The three-dimensional printing–a modern techno-logy used for biomedical rototypes.* Materiale plastice, *47*(3), pp.328-334.

[18] Geonea, I.D.; et al., *Dynamic Analysis of a Spherical Parallel Robot Used for Brachial Monoparesis Rehabilitation*. Applied *Sciences,* 2021, *11*, 11849.

[19] Tarnita, D., Georgescu, M., Tarnita, D.N., *Applications of Nonlinear Dynamics to Human movement on Plane & Inclined Treadmill*, New Trends in Medical and Service Robots, Vol 39, 59-73, 2016.

[20] Tarnita, D., Geonea., I.D., et. al. *Analysis of Dynamic Behavior of ParReEx Robot Used in Upper Limb Rehabilitation*, Appl. Sci., 12(15), pp. 7907, 2022.

Analiza cinematică a mișcării degetului uman și robotic folosind teoria WAVELET

Rezumat: În această lucrare s-a făcut analiza cinematică a mișcării de flexie-extensie a degetului uman și a unui deget robotic, fiind comparate rezultatele folosind tehnica descompunerii semnalului cu ajutorul funcțiilor și teoriei wavelet. Lucrarea propune o metodologie de evaluare a cinematicii articulațiilor formate între falangele degetului uman și ale unui deget robotic prin compararea energiei de detaliu a semnalului.

Cuvinte Cheie: *deget uman, deget de robot, cinematica, teoria WAVELET, biometrica, goniometrie*

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