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COMPARING THE HEATING RATE OF THE PROXIMAL PHALANX OF THE FINGERS IN RHEUMATOID ARTHRITIS AND HEALTHY SUBJECTS

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Abstract: Thermography is a non-invasive imaging technique that has been used for the assessment of rheumatoid arthritis (RA). The purpose of this research was to compare the heating rate of the proximal phalanx of the fingers and the whole palms in RA and that of healthy subjects. The study was conducted on 48 patients with high disease activity, hospitalised for RA, and 45 healthy subjects. The thermograms were taken with the FLIR camera E60bx. Subjects were instructed to immerse both hands up to the wrist in water thermostatically controlled at 0°C for 30 s. Then, the hands were pulled out of the water; the warm-up period was 180 s. Image pre-processing included: segmentation, extraction and anatomy identification. The mean value of the heating rate for whole palms and the proximal phalanx of the fingers in the RA group was lower than that in the control group ($p < 0.05$). This coincides with the uneven flow of the heat-transfer blood caused by the disease. However, the difference between the heating rates of the proximal phalanx of the fingers was greater than that of the entire hand. In addition, the proximal phalanx heating rates of the second, third and fourth fingers were higher than those of the outermost two fingers. The study may be used to develop clinical tools in the detection of abnormal heat signatures in the phalanx proximal of the fingers.

Key words: active thermography, rheumatoid arthritis, proximal phalanx, image processing

1. INTRODUCTION

Thermography is a non-invasive imaging technique that has been used for the assessment of rheumatoid arthritis (RA) in recent years. It is a promising tool for the early detection and monitoring of RA, as it can detect changes in temperature distribution and blood flow associated with inflammation in affected joints [1-4]. The state-of-the-art approach for thermography imaging in rheumatoid patients typically involves the use of high-resolution infrared cameras to capture thermal images of the affected joints. These images are then processed using advanced image-processing techniques to extract temperature and blood flow information [4-7]. Recently, research has focused on the development of machine learning algorithms that can automatically analyze thermography images and provide quantitative measurements of disease severity. These algorithms use deep learning techniques to extract features from the images and can accurately classify patients based on disease severity [8-9]. Some common methods include image segmentation [10] e.g. active contour models, superpixel-based methods, and deep learning algorithms to accurately identify and isolate the regions of the image corresponding to inflamed joints or regions of interest, to facilitate the quantification of disease activity and response to treatment. Some studies explored [11] various methods for feature extraction in thermal images of RA patients, including identifying hotspots, quantifying temperature changes and analysing blood flow patterns. Several researchers have written about the classification in RA to prediction disease activity and treatment response [12-18]. The authors explored various methods for classification of RA disease activity based on thermography images, including using machine learning algorithms such as deep learning, support vector machines and decision trees. Studies [19-23] explored various methods for image fusion in RA, including combining different modalities of imaging such as thermal imaging, ultrasound and magnetic resonance imaging (MRI) in aim to improving the accuracy of diagnosis and assessment of RA by providing a more comprehensive and detailed view of the affected joints and surrounding tissues.

In healthy individuals, the skin temperature of the proximal phalanx of the fingers is typically regulated by factors such as environmental conditions and overall blood flow. Individual variations can occur, but significant heating or abnormal temperature patterns are not typically observed in the absence of any underlying pathology. The degree of temperature elevation can vary depending on the severity of inflammation and disease activity. In RA, joint inflammation and damage can lead to increased blood flow and warmth in affected joints [24-26], but there have been no studies comparing the heating rate of the healthy and RA fingers. The purpose of this research was to compare the heating rate of the proximal phalanx of the fingers and the whole palms in RA and healthy subjects. Consequently, the results may deliver tools for the detection of abnormal heat signatures in the phalanx proximal of the fingers.

2. METHODS

2.1. Subjects

The study was performed at the University Clinical Hospital in Białystok [5,6]. The measurement was taken for a total group of 48 patients with high disease activity hospitalised due to RA. The criteria for patients' inclusion were: age >18 years, and duration of anti-rheumatic biological therapies over 1 year. The exclusion criteria were: age <18 years old, and non-biological therapies. The control group was 45 healthy subjects. The patients participated in the study with their consent, according to the declaration of Helsinki. The Polish Regional Committees have approved this study for Medical and Health Research Ethics.

2.2. Measurement protocol

The subjects were asked to not consume alcohol or caffeinated drinks for 24 hours, smoke for 2 hours, and exercise for 1 hour before the image-acquisition phase. All subjects were introduced to the infrared camera and the course of the study. Next, the subjects' images for the affected joints of the hand were captured. The patients were instructed to immerse both hands up to the wrist in water thermostatically controlled at 0°C for 5 s; the local skin temperature dropped by 4–5°C and is stable [5,6]. Then removed their hands from the water, and the rewarming period was for 180 s, Fig. 1. The water temperature was continuously monitored with a digital thermometer. The thermograms of the hand fingers for each subject were taken by an experienced experimenter to ensure both rigor and repeatability [25] with the FLIR thermal imaging camera E60bx (Systems Inc., USA) with a resolution of 320 × 240 pixels and thermal sensitivity of <0.05°C, following the guidelines of the American Thermology Association. Thermography images were taken in a controlled environment (air humidity 55%, emissivity 0.98 with stable temperature 23±1°C and minimal airflow). FLIR Tools software for the analysis of images was used.

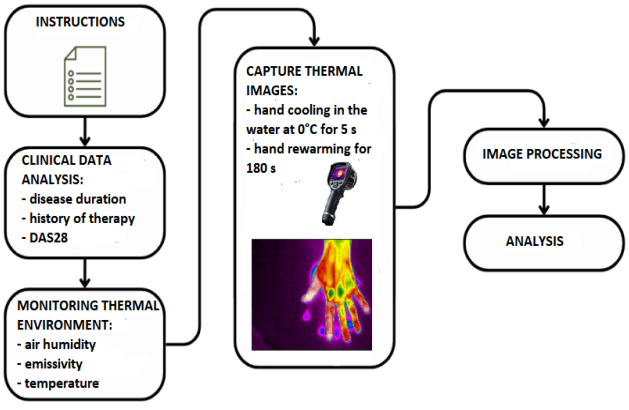

Fig. 1. Flowchart of the investigation procedure.

The heating rate of the proximal phalanx of the fingers (Fig. 2) was analysed in two steps: (1) hand cooling; and (2) hand rewarming.

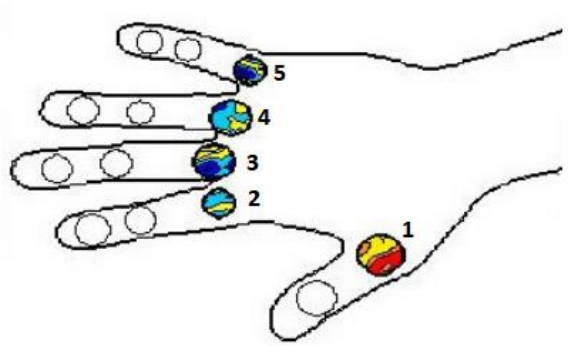

Fig. 2. Definitions of the regions of interest used in this study: 1 – Pollex; 2 – Index; 2 – Medius; 4 – Annularis; 5 – Digitus minimus.

2.3. Image processing

The temperature data was considered as two-dimensional matrices $L_i: w \times h \to T_i$, where w and h determine the frame size in Cartesian coordinates $x = 0..\ w$, $y = 0..\ h$, and the number of frames are $i = 1..\ n$. Secondly, the data were used as a table function. The frame number corresponds to the time $t = 0..\ t_n$. Therefore, $L_i: w \times h \to T(x, y, t)$. In this case, the temperature measured at the initial state of a hand represented only one frame, which means that $i \equiv n = 1$. Therefore, $L_{init}: w \times h \times 1 \to T_{init}$. Each frame contains information about the temperature of two objects: hand and a background. At the first stage, a hand was separated from a background. Anjos [27] proved that the balanced histogram thresholding method delivers good results for segmentation of the frame L_{init} and the frame L_n, and contains information on the completion of the heating process of pre-chilled hands (Figs. 3 and 4a). The change in the hand temperature from the first measurement to the last was determined as below:

$$\Delta T(x, y) = T_n\ (x, y) - T_1\ (x, y). \tag{1}$$

In case of uniform and incomplete heating, the heating rate was determined according the formula [27]:

$$v'(x, y) = \frac{\Delta T(x,y)}{t_n}. \tag{2}$$

We assumed that the temperature peaks are reached not simultaneously at different points of the surface. Consequently, the instant of the temperature peaks in the points are $t^j_{\max} \le t_n$, where $j = 1..\ w \times h$ is a number of element of a two-dimensional matrix L_i, corresponding to a pair of Cartesian coordinates (x, y) of the point on the surface. Therefore, $T\left(x, y, t^j_{\max}\right) \ge T\left(x, y, t^j_n\right)$. If $T(x, y, z)$ is a three-dimensional function of temperature in some heat-conducting medium, but the temperature varies only along one axis 0Z, then the density vector of the heat flux transferred by the thermal conductivity is proportional to the temperature gradient vector $q \propto -grad(T) = -\bar{e}_z\, {\partial T}/{\partial z}$. The function of temperature is also three-dimensional, and the temperature varies only along one axis 0 t too. In a general case, the heating rate at each point on the surface by differentiating the temperature function with respect to time is obtained as follows (Fig. 4b):

$$v(x, y) = \frac{\partial T(x,y,t^j)}{\partial t}, \quad t^j = 0..\ t^j_{\max}. \tag{3}$$

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The vector function $v(x,y)$ reflects the processes of heating in more detail than the distribution of the scalar values of the instants (Fig. 5). It is a two-dimensional vector field; therefore, a divergence of the heating rate field must be found (Fig. 6):

$$div\big(v(x,y)\big) = \nabla \cdot \frac{\partial T(x,y,t^j)}{\partial t}, \quad (4)$$

$$div\big(v(x,y)\big) = \frac{\partial}{\partial x} \cdot \frac{\partial T(x,y,t^j)}{\partial t} + \frac{\partial}{\partial y} \cdot \frac{\partial T(x,y,t^j)}{\partial t} + + \frac{\partial}{\partial t} \cdot \frac{\partial T(x,y,t^j)}{\partial t}. \quad (5)$$

The partial derivatives of the heating rate with respect to the Cartesian coordinates are zero because the heating rate vector is orthogonal to the axes $0X$ and $0Y$:

$$div\big(v(x,y)\big) = \frac{\partial}{\partial t} \cdot \frac{\partial T(x,y,t^j)}{\partial t}. \quad (6)$$

2.4. Statistical analysis

The temperature data were presented as means and standard deviations (SD). To verify the hypothesis of a normal distribution of the analysed variables, the Shapiro–Wilk test was used. To further analyse variables with normal distribution, a parametric test (Student's test) and other nonparametric tests were used. Statistical analyses were performed using Statistica software version 13.1 (StatSoft, Poland).

3. RESULTS

The mean age for healthy subjects was 52.9 ± 4.2 years and for RA patients was 52.3 ± 5.4 years. The image data were recorded on 5,400 frames (thermograms). The initial temperature (hand cooling) and final temperature (hand rewarming) are presented in Fig. 3 and in Tab. 1.

Tab. 1. The temperature (standard deviation) during hand cooling and hand rewarming in the control group and RA patients, [°C] ±SD

Phalanx proximalis	Control group		RA group	
	cooling	rewarming	cooling	rewarming
Pollex	23.5 (1.75)	29.5 (1.95)	23.0 (2.75)	29.5 (2.45)
Index	24.2 (2.40)	32.0 (1.75)	23.0 (2.35)	31.5 (1.35)
Medius	24.0 (2.10)	32.5 (2.15)	23.5 (1.60)	30.5 (2.15)
Annularis	23.5 (1.90)	32.3 (1.95)	24.0 (2.50)	31.0 (1.75)
Digitus minimus	23.0 (2.50)	31.0 (1.65)	22.0 (1.80)	31.0 (2.75)

The process is stationary, and its parameters are stable at any time interval. This is a consequence of the ability of a living organism to maintain viability.

Fig. 4a shows the coldest and the warmest temperature of a subject hand as well as the diagram of the average values of the frame sequence that reflect the process of the subject's hand heating (Fig. 4b).

Fig. 5 shows the time spatial distributions to reach temperature peaks at points ($t^j_{\max}$) and the heating rate at each point ($v(x,y)$) of the subject's hand.

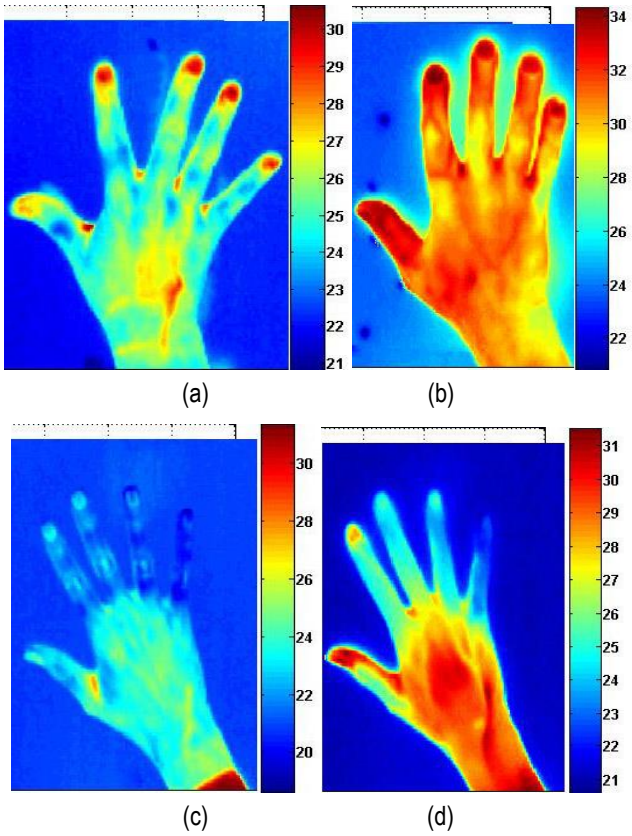

Fig. 3. Thermogram: (a) hand cooling in typical; (b) hand rewarming in typical; (c) hand cooling in RA patient; (d) hand rewarming in RA patient. RA, rheumatoid arthritis.

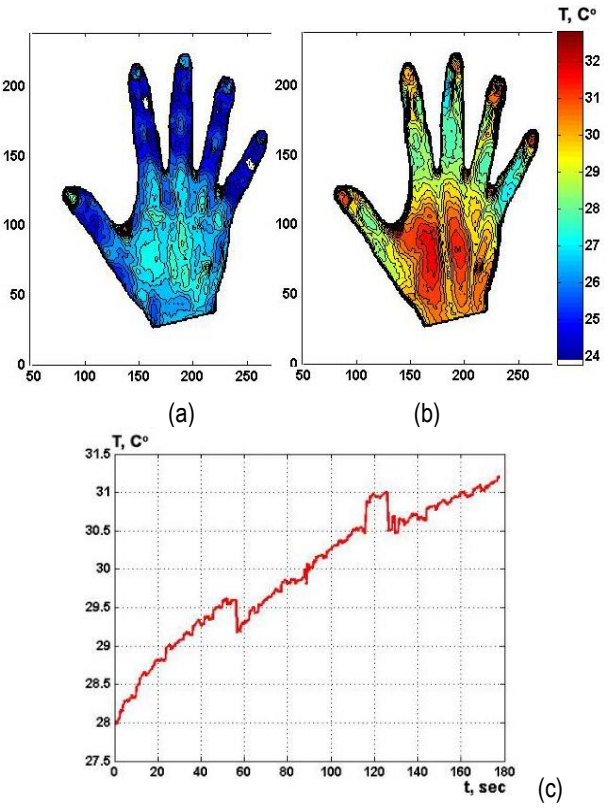

Fig. 4. The thermograms after segmentation: (a) the coldest and the warmest temperature of a hand; (b) a diagram of the heating rate.

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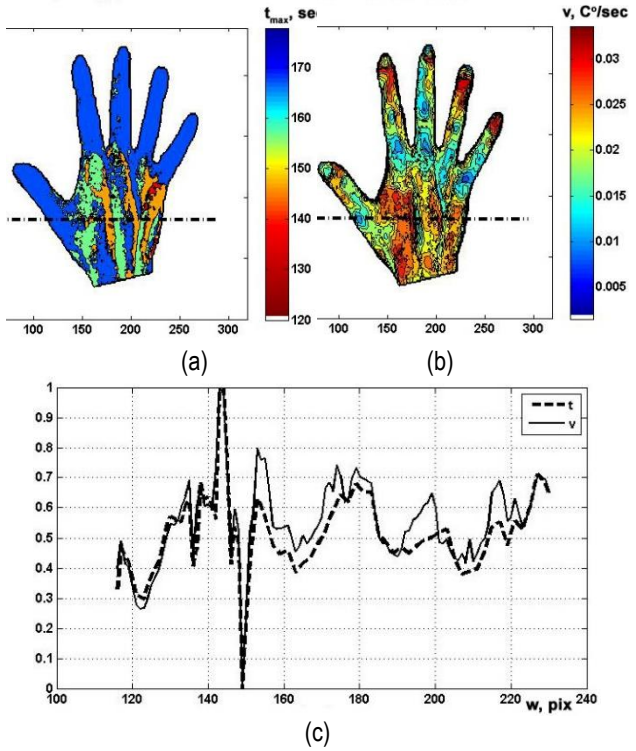

Fig. 5. Space distribution: (a) the time of the temperature peaks; (b) the heating rate; (c) the cross-sections of the time and the heating rate

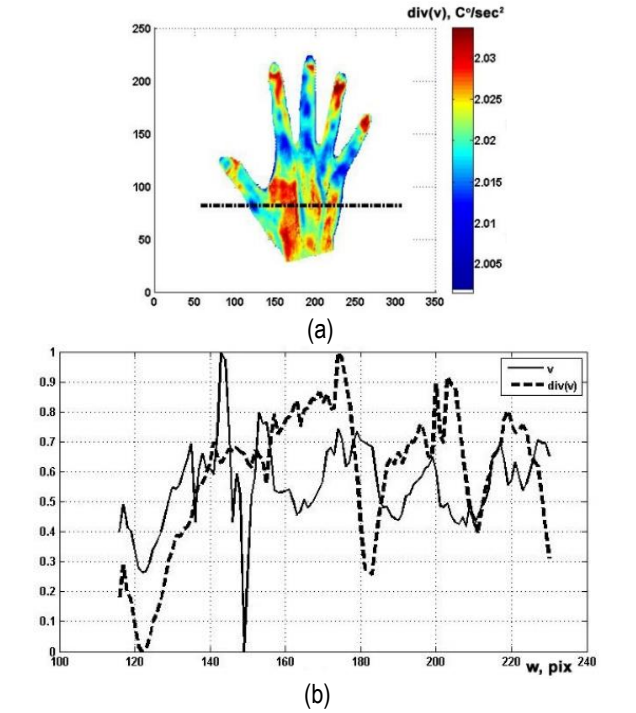

Fig. 6. The divergence of the heating rate: (a) space distribution; (b) the cross-sections of the heating rate and its divergence.

The divergence of the heating rate (Fig. 6a) shows the density of the sources of the central field of the heating rate at each point of the heated surface of the hand. Fig. 6b shows the normalised cross-sections of the heating rate and its divergence.

The maximum temperature on the thermograms was reached at different times in restoring the hand's temperature after cooling. Therefore, it can be assumed that the rate of temperature increases (degree/min) at the points will not be the same. The heating rate depends on the spatial distribution of the inflow of the coolant (blood) and may be an important diagnostic parameter. At the first stage of the study, we did not take into account the anatomical correlation of the heating rate at the measured points but analysed the static parameters of the distributions. Typical histograms of the heating rate at the points of the image of the hand are shown in the images (Fig. 7). The rate of temperature rise (degree/min) is reflected in the x-axis. The values of the y-axis are normalised to the distribution integral, which made it possible to impose a Gaussian curve on the histogram.

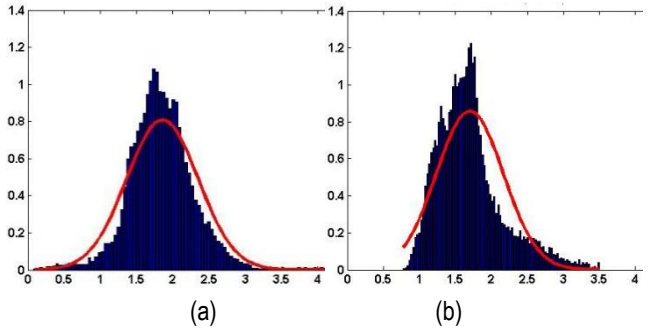

Fig. 7. Histograms of the heating rate (degree/min) at the points of the hand image: (a) control group; (b) RA. RA, rheumatoid arthritis.

Mean and SD were used to compare the distributions of the heating rate of people with RA and a control group of healthy people (Tab. 2). The average value in the RA group was slightly less than in the control group. The SD of the RA group was greater than that of the control group and was significant ($p < 0.05$). This is in good agreement with the uneven flow of the coolant (blood) caused by the disease.

Tab. 2. The parameters of the heating rate of hand by groups (RA, rheumatoid arthritis; SD, standard deviation)

Groups	Mean ($p > 0.05$)	SD ($p < 0.05$)
Control	1.865	0.292
RA	1.711	0.552

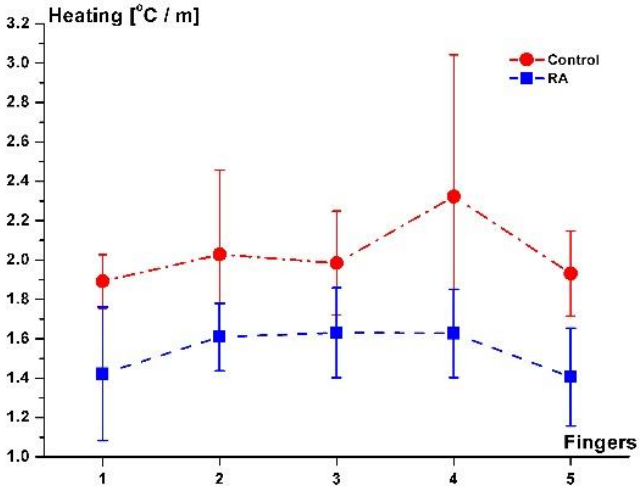

Fig. 8. The heating rate (degree/min) of proximal phalanx of the fingers ($p < 0.05$). RA, rheumatoid arthritis

The next stage of the study was the localisation of the assessment of the heating rate in the anatomically important areas of the hand. The technique of finger extraction by skeletonisation has been described in Ref. [6]. We identified areas corresponding to the phalanges on the pre-discovered midlines of the fingers. Fig. 8 shows the heating rate of the proximal phalanx of the fingers ($p < 0.05$).

The heating rates of the control group were higher than those of the RA group, as well as the average heating rate of the hand as a whole. The difference in heating rates between the two groups on the proximal phalanx of the fingers was more than the difference between these groups across the whole hand. The heating rates of the proximal phalanx of the fingers 2, 3 and 4 were more than that of the two outermost fingers.

4. DISCUSSION AND CONCLUSIONS

Recent studies have investigated the use of thermography to detect early signs of joint inflammation in RA patients before the onset of visible joint damage. Some studies [2,3,6] found that thermography was able to detect joint inflammation in RA patients with normal physical exam findings, suggesting its potential as a sensitive screening tool. Other studies have also looked at the use of thermography to monitor disease activity and treatment response in RA patients [7,8]. In RA, the joints of the fingers are commonly affected, including the proximal interphalangeal (PIP) joints. That's why we decided to compare the heating rate phalanx proximal of the fingers in RA and healthy subjects. Previously, active thermography has been used in research studies to investigate the thermal properties of joints in RA patients [28]. In these studies, a dry cooling of the skin for 1 min was used to induce a thermal contrast on the joint, which was then measured with an infrared camera. Other heat sources, such as surface cooling with a mixture of CO2 and air from a cryotherapy unit and also laser or microwave heating, may be more suitable in some cases [29]. In all cases, it is very important to follow established measurement protocols and safety guidelines. We used water as a heat source in active thermography studies [5,6] to minimise thermal exposure to the patient. In Ref. [5], the outcomes included the mean temperature of five fingers of a hand: In static, post-cooling, and post-rewarming, the total change in mean temperature of fingers due to cold provocation, the total change in mean temperature of fingers due to rewarming, the area under the cooling curve, the area under the heating curve, the difference between the area under the rewarming and the cooling curve, and temperature intensity distribution maps. For patients with high disease activity, a lower area under the heating curve and a lower difference between the area under the rewarming curve and the cooling curve were observed, as well as a smaller total change in mean temperature due to rewarming, compared to patients with moderate disease activity. In turn, the study [6] proved that the cold provocation test discriminates between RA patients and controls and detected inflammation in RA patients by the measurement of temperature profiles along the fingers using an infrared camera.

This study examines the dynamical change in the temperature field over time. Integral parameters were also taken into account, as well as parameters of specific anatomical areas. We found that there were significant differences in the heating rate on the phalanx proximalis of RA patients and healthy control subjects. Specifically, the RA-affected joints had lower peak temperatures and slower cooling rates compared to the healthy joints. The use of water as a heat source in active thermography for RA patients has some limitations. RA patients may have joint deformities, inflammation and other conditions that can affect the thermal properties of the joint and the ability of water to induce a thermal contrast.

Overall, these studies suggest that active thermography can be used to detect thermal differences between RA-affected joints and healthy joints in the same patient and may have the potential as a non-invasive tool for monitoring disease activity and treatment efficacy in RA.

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