Genetic Algorithm Based Heuristic Measure for Pattern Similarity in Kirlian Photographs

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Abstract

This paper presents the use of a genetic algorithm based heuristic measure for quantifying perceptable similarity of visual patterns by the example of Kirlian photographs. Measuring similarity of such patterns can be considered a trade-off between quantifying strong similarity for some parts of the pattern, and the neglection of the accidental abscense of other pattern parts as well. For this reason, the use of a dynamic measure instead of a static one is motivated. Due to their well-known schemata processing abilities, genetic algorithm seem to be a good choice for "performing" such a measurement. The results obtained from a real set of Kirlian images shows that the ranking of the proposed heuristic measure is able to reflect the apparent visual similarity ranking of Kirlian patterns.

1 Introduction

Kirlian photography was invented in the former Soviet Union in 1939 by Semyon Kirlian [KK64]. Due to the fact that images obtained through the Kirlian process seems to reveal aura-like features around living objects, it has a long time fascinated scientists and laymen, but charlatans as well. The Kirlian process and a number of processes derived later based on the original one all use high frequency, low current electricity to create an electrical "corona" around the object to be photographed. Actually, the discharge is photographed. It has been suspected that Kirlian photographs reveal relevant medical information about the "energetic" state of the object, esp. the human body or parts of it, and can be used for the diagnosis of disease [Cho96] [Kon97] [Omu77]. The medical term for such a diagnostic method is electroradiography. One well-known approach to a therapy based on Kirlian photography was introduced by Mandel [Man83], but there are more [PKF76].

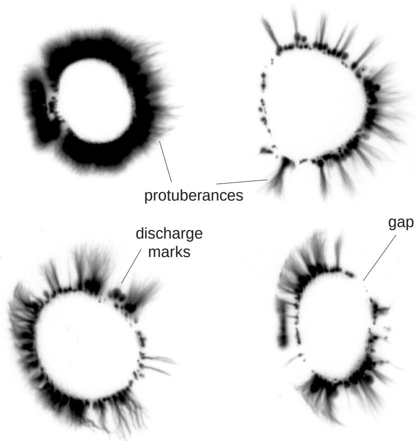

Figure 1: Kirlian images of fingertips of four different subjects.

In fig. 1 the Kirlian photographs of four different subject's fingertips can be seen. There are typical features of such photographs, as protuberances, gaps and discharge marks. All of them give the human observer of such images the impression of a unique pattern category. However, a serious controversy is raging among researchers on the "non-random" nature of Kirlian images, especially the question, whether the Kirlian images of one and the same person show similar features or not. In some cases, as it is shown in fig. 2, a visual similarity of images taken from the same person at different moments can be clearly seen. Already this fact urges an explanation.

This paper presents an approach to the quantification of the visual similarity of Kirlian images. Due to the different sources of influence on the picturing process, standard statistical methods will not give very much qualitative insight into this issue (see [Tre97] [Tre98] for a study using conventional statistics). Consider for example the presence of gap features in the pattern. Gaps could appear for two different reasons: as partly belonging to the suspected person-specificity of the Kirlian image, or as being caused by a random influence on the individual picturing process. Hence, gaps could stand for visual similarity or not. Also, the local distribution of discharge marks could appear differently. Of more importance is the *partial* high similarity, thus giving a contradictory goal for similarity measurement. A means for reflecting *schematical* similarity has to be used instead of a direct computation from image data.

In order to solve this problem, a dynamic measure is used instead of a static one. The similarity is ranked by the degree, to which it is possible for an adaptive procedure to re-establish that similarity. Genetic algorithms are proposed for fulfilling this task.

In section 2, the necessary preprocessing of the Kirlian images and the used

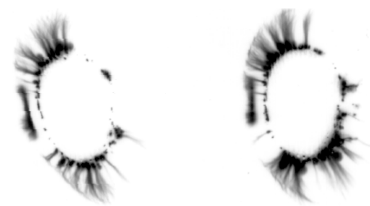

Figure 2: Kirlian images of the same fingertip of a subject, taken at different moments.

material are presented. Section 3 discusses the problem of processing measures and emphasizes the use of a genetic algorithm based heuristic measure for the purpose of this study. Finally, in section 4 the results on the Kirlian images, which were achieved with this approach, are presented and discussed.

2 Material and method

From 30 adult subjects, which suffered from several diseases, 120 Kirlian images were taken, four images of the hands and feets of each subject, with 15 minutes time delay between two photographs. Out of those 120 examinations, 32 were selected according to an apparent high visual similarity of at least three fingertips. The goal was to provide a quantitative measure that reflects this visual similarity, and which is able to separate the class of Kirlian images from random patterns and may hint on person-specificity. The goal was not to relate the Kirlian images to the special diseases of the subjects.

The Kirlian images were digitized using a resolution of 400dpi. As a result, there were 96 digital images (four images of three fingers of eight subjects) prepared for further examination.

In order to get a comparable representation for all those images (which are differing in size, quality and presence of features), an unrolling procedure was applied, with an interactively set center. Thus, the nearly circular structure of the Kirlian patterns is reflected. For 256 equally-angled directions, the distance between the first and last group of pixels[1], which was meet along that directions, was taken and plotted against the direction angle. This "coarse polar transformation" gives a pattern, which will be referred to as signature of the Kirlian image in the following (see figure 3). When there was no group of pixels found, the value 0 was assigned to the corresponding direction.

The reason for unrolling the Kirlian images were

- normalization of the results,
- reduction to the one-dimensional case,
- first quantification of the image data,

[1]At least three pixels in a sequence are black.

- noise reduction,
- accounting for shape irregularity and
- special treatment of gaps.

The unrolled Kirlian image signatures were used for further processing.

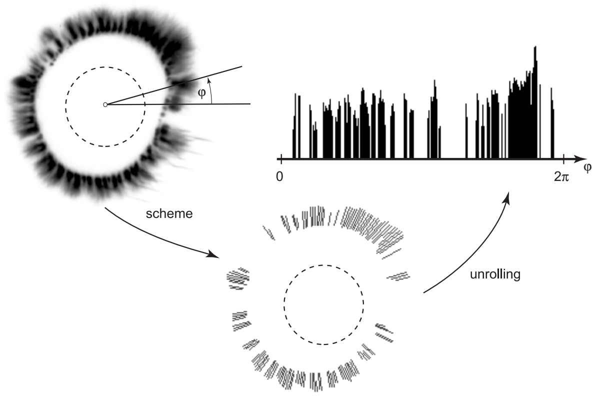

Figure 3: Unrolling of a Kirlian image.

3 Genetic algorithms for heuristic measuring

In figure 4, four Kirlian signatures of two different subjects can be seen. While there is still an apparent schematic similarity of the signatures of the same subject, and an obvious dissimilarity for signatures of different subjects, the provision of a suitable measure to measure this is not so easy. The idea was to use an adaptive procedure for such a measuring. The adaptive task here is given by the goal to design a signature, which *is equal* to all four signatures at once. Of course, this task has no exact solution, but there will be an optimal one. The matching quality can be used as a measure of similarity. Instead of being a static measure, such a procedure can be considered a dynamic measure. In artificial intelligence research, such measures are infrequently used and referred to as heuristic measures.

To provide an analogy for the heuristic measure approach: consider the task to get to know, whether a given lake is deep or shallow. An easy way would be to measure the depth of the lake at every point, then to compute the average depth and decide from the obtained value. However, the effort might be too high for getting the depth everywhere. So, the other approach is to instruct a subject to swim to a shallow position of the lake, starting of from a random position. The subject may use all of her skills to solve this task. Then, the subject is repeatedly placed anywhere in the lake, and a couple of minutes is

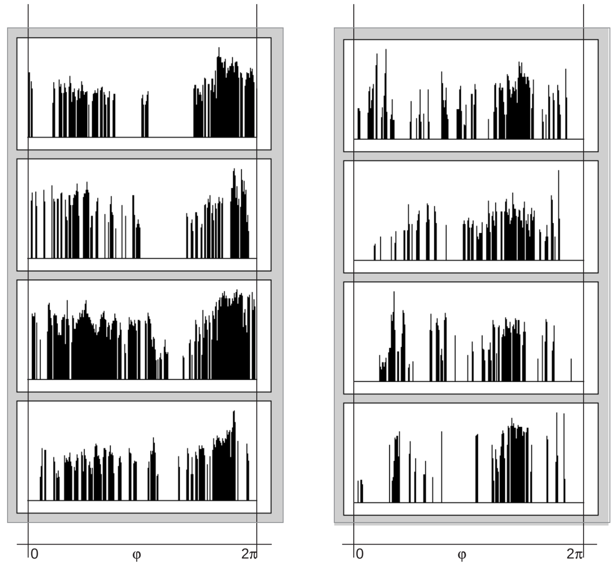

Figure 4: Unrollings of two sets of Kirlian images.

given to her to find to a shallow place. Now, it is counted how often the subject was able to find a shallow place among all trials. From this frequency, the depth of the lake can be judged. This gives a *heuristical* measure for the depth of the lake.

It has to be noted that the actual size of the measure is not of interest, since this value depends on the method used for the adaptation. What counts is the relative ranking of those values for different objects, say different lakes. It follows that for a reasonable use of such a measuring, the measure needs to be calibrated to the applied method, e.g. on lakes, which are known to be very deep or very shallow. Then, the obtained values can be related to the wanted information.

Back to the Kirlian images, as a prominent heuristical search procedure, genetic algorithms (GA) were chosen. GAs are well-known for their inherent building-block (or schemata) processing capabilities, which exposes them among other optimization procedures [Hol75] [Gol89].

GA maintain a population of *bitstrings*, i.e. vectors composed of the elements 0 and 1. A *schema* is a bitstring containing "wildcards", i.e. a bitstring with some unspecified positions. In this sense, e.g. 1011 is a realization of the schema 1**1, and 0111 not. During the GA run, not only the space of bitstrings (so-called *searchspace*) is searched for better bitstrings (solutions), but the space of all schemata as well. This was a long time suspected the "hidden force" that drives GA towards successful solutions, and it was initially formulated as [Bal94]:

Short, low order, above average schemata receive exponentially increasing trials *in subsequent generations.*

However, there were prominent failures of GAs as well, and the question about the importance of building blocks and their features for genetic search is a still ongoing research topic by itself (see [SW99] for a newer work in this field).
From this, the possible ability of a GA to find building blocks (at least reflected by the obtained results) that match a set of different bitstrings as close as possible can be expected. The fitness of a bitstring is the average hamming distance of the bitstring to the given set of bitstrings. The average fitness obtained from the best individuals of several runs of a GA on the bitstring matching problem is a heuristic measure for schematic similarity of the given set of bitstrings.

It has to be noted that the use of standard statistical measures for Kirlian images was considered in [Tre97] and [Tre98], yielding no insight into the similarity of the patterns. This is no wonder, since the possible absence of features, despite of a present high similarity in all other parts of the pattern, may deceive direct computations.

A similar procedure for solving a pattern recognition problem was presented in [KWN97]. There, in a system for automatic processing of invoices, the schematic similarity (but not equality) of invoice table rows was detected by running a genetic algorithm for a few generations, with the task of generating a bitstring pattern for *all* text rows of the document at once. The GA was able to detect the group of rows comprising an invoice table by using this method. However, when there was no invoice table present within the document image at all, the achieved fitness value remained below a certain threshold. This can be considered a heuristically measuring based extraction of invoice table from the invoice document image as well.

4 Results and discussion

For heuristicically measuring the schematic similarity of four signatures, those signatures were represented as four bitstrings of length 256. The bitstrings at position i were set to 1, if the value of the signature at the i-th angle (i.e. at angle $2\pi i/256$) was over 50% of the maximum value of the signature, and to 0 if this was not the case.

For the GA, a population of 10 bitstrings of length 256 was used. The genetic operations were roulette-wheel selection, one-point crossover, pointwise mutation and elitist selection. The fitness measure for a bitstring was the average hamming distance of the bitstring to the four bitstrings, which were derived from the four sigtnatures. However, for the hamming distance only positions of the signature bitstrings were regarded, for which the left and right neighbors carried the same bitvalue. In each generation, 30 children were generated, and 200 generation cycles were performed at all. The average fitness of the best individuals, taken over ten runs of the GA, gave the heuristical measure for signature similarity.

In order to "calibrate" the GA-based heuristical measure, two experiments were performed in advance. In one experiment, the procedure was applied to 4-tupel of random patterns, i.e. random sets of 256 values from $[0, 1]^2$. The average best fitness values of those runs were between 0.2578 and 0.2930.

In a second experiment, the same was done with four randomly selected Kirlian images (i.e. Kirlian images of different subjects). This time, values between 0.2815 and 0.3164 were obtained, thus notably higher values as for the random patterns.

Table 1: Result of the Genetic Algorithm based heuristic measure for Kirlian images of the same person.

Finger	Measure	Finger	Measure
K3-l2	0.503625	K13-l3	0.437500
K3-l3	0.410156	K13-r4	0.351563
K3-r3	0.476562	K13-l1	0.445312
K5-r2	0.398437	K15-l3	0.347656
K5-l3	0.503906	K15-r3	0.363281
K5-r3	0.500000	K15-l4	0.441406
K6-r2	0.496094	K18-l4	0.488281
K6-l4	0.406250	K18-l1	0.515625
K6-r1	0.441406	K18-r1	0.523437
K11-l2	0.523437	K19-l2	0.394531
K11-r2	0.429687	K19-r2	0.441406
K11-l3	0.371094	K19-l3	0.386719

Table 1 gives the results for the final experiment with the test subjects. All measures are above 0.34 and can be considered to be clearly distinct from random patterns and from pattern groups of several subjects.

The study shows a clear ranking: at the lowest level, there are random patterns; at the next level, there are inter-subject Kirlian patterns; and on the highest level there are intra-subject Kirlian patterns. The heuristic measure correctly describes the visual similarity of the intra-subject Kirlian photographs.

The question, whether this hints on a person-specificity of Kirlian images at all should be discussed with care. At least, there is person-specificity for the selected patterns. According to the heavy scientific attacks on electroradiographic therapies in general, this reflects the fact that there are at least some circumstances, where Kirlian images of the same person are more similar to each other than to Kirlian images of different persons. From a physical point of view, this is an astonishing fact. While the basic physical mechanisms of the corona discharge are fully understood, there is no proper model for the appearance of the typical features of a Kirlian image for the same person. However, two

[2] Note, that the order of magnitude of the values does not influence the heuristical measure.

applications of even low person-specificity of Kirlian images are nevertheless of high interest: for biometrical applications, and for clinical therapies based on the feedback of a subject to its own Kirlian image.

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