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An overview of iris recognition: a bibliometric analysis of the period 2000–2012

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Abstract Person identification based on iris recognition is getting more and more attention among the modalities used for biometric recognition. This fact is due to the immutable and unique characteristics of the iris. Therefore it is of utmost importance for researchers interested in this discipline to know who and what is relevant in this area. This paper presents a comprehensive overview of the field of iris recognition research using a bibliometric approach. Besides, this article provides historical records, basic concepts, current progress and trends in the field. With this purpose in mind, our bibliometric study is based on 1,354 documents written in English, published between 2000 and 2012. Scopus was used to perform the information retrieval. In the course of this study, we synthesized significant bibliometric indicators on iris recognition research in order to evaluate to what extent this particular field has been explored. Thereby, we focus on foundations, temporal evolution, leading authors, most cited papers, significant conventions, leading journals, outstanding research topics and enterprises and patents. Research topics are classified into three main categories: ongoing, emerging, and decreasing according to their corresponding number of publications over the period under study. An analysis of these indicators suggests there has been major advances in iris recognition research and also reveals promising new avenues worthy of investigation in the future. This study will be useful to future investigators in the field.

Keywords Iris biometrics · Iris recognition · Bibliometric study

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Introduction

For a long time, man has tried to gain control over the access to specific places or important information. Among other systems, the use of light signals, hand signals, voice signals, royal stamps, safe conduct or keys have helped to limit access to key places and information. With the emergence of new technologies of information and communication, other systems have been developed such as pass codes, passwords and smart cards. In recent years, new biometric technologies have arisen as more reliable control access systems are required. This robust technology is based on the premise that each individual possesses physiological and behavioural features which are unique (Jain et al. 2004). Fingerprints, hand geometry, face, ears, retina and the iris constitute a few examples of these physiological features. As far as behavioural features are concerned, some unique features are: keystroke, voice, signature and gait. Hence, the traditional systems have given way to biometric technologies.

Iris recognition has gained more popularity among the modalities used for biometrics recognition in the last decade. This is due to its characteristics: its rich texture is endowed with many degrees of freedom; it remains unchanged despite the ageing process; it is protected by a structure which, if modified, may compromise the health of the individual. Besides, it may be easily accessed with a non-invasive device (Li and Jain 2009). Therefore, many leading companies in the field of security aim to introduce this technology on the market and to diversify its applications.

The idea of using the iris for person identification dates back to the end of the nineteenth century. In 1892, the inspector Alphonse Bertillon of the police department in Paris, developed a study (Bertillon 1892) on the use of three main classes of iris to identify convicts. Later on, the ophthalmologist Burch in 1936 (Daugman 2001) presented new evidence of the advantages of using the iris for person identification. The ophthalmologists (Flom and Safir 1987) documented and patented the general concept of iris recognition a few decades later. From these assumptions, the professor John Daugman (1994) developed the first algorithms for iris recognition in 1989 and patented them in 1994. Hence, John Daugman is considered as the pioneer in iris recognition and his inventions underlie all the research in the field.

Nowadays, an increasing number of institutions and young researchers are betting on the potential of iris recognition for the future. Consequently, an adequate methodological approach is required to identify from the existing literature the most promising areas of research. To this end, studies aiming to summarize the state of the art on iris recognition have been undertaken (Bowyer et al. 2008; Sheela and Vijaya 2010). These previous studies rely on qualitative methods or subjective assessment. In order to identify the core and the trends in the field, a more quantitative approach is needed such as the bibliometrics one we decided to adopt in our study. The bibliometric methodology refers to the generalization of the use of the statistical bibliography proposed by Hulme in 1923 and later developed by Pritchard (1969). Using statistical techniques, this approach relies on the quantitative study of specific factors to extract relevant information from bibliographical records. The quantitative study of these specific factors allows to assess the evolution of a particular scientific field, in this case: iris recognition. It has been used in a variety of fields such as: world university ranking (Chen and Liao 2012), solar power (Dong et al. 2012), aquaculture literature (Natale et al. 2012), information literacy in social sciences and health sciences (Pinto et al. 2012), university-industry links (Teixeira and Mota 2012) and GPS research (Wang et al. 2013). In spite of its benefits, the bibliometrics approach has been under-used mainly because of lack of knowledge of the discipline.

Our paper will provide a useful overview of iris recognition research for newcomers to the field. Our objective is to overcome the shortcomings of the subjective approach of the previous studies. Our study focuses on basic concepts, historical records and trends on iris recognition within the framework of the bibliometrics approach. It is based on an information retrieval of 1,354 documents in English which have been published, during the period 2000–2012, as a product of significant conventions and by journals of high impact, all indexed by Scopus. This bibliometric study accounts for a number of issues: foundations, temporal evolution, leading authors, most cited papers, significant conventions, leading journals and outstanding research topics of the field of iris recognition. The outstanding research topics are classified into three categories: ongoing, emerging, and decreasing according to their corresponding number of publications over time. Each issue was developed using histogram graphs, collaborations networks, self-organized maps (SOM) and tables.

The overall structure of this paper is as follows: section two describes in a condensed fashion the foundations of iris recognition. Section three provides the outline of the methodological approach used in this research. The results and discussion of our bibliometric study follow in section four. Finally, section five presents the conclusions of our study.

Foundations of iris recognition

Iris anatomy

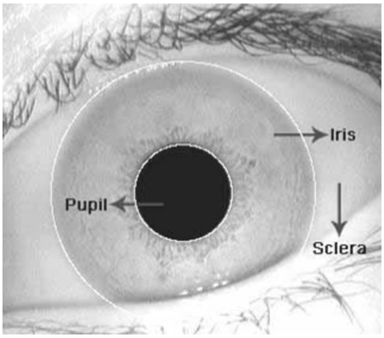
The iris is an internal organ of the eye located behind the cornea and the aqueous humour. By observing the iris from the center of the circle which models the inner boundary up to its outer boundary, two delimiting borders can be identified (see Fig. 1). The first one, pupil—iris border, is defined by the shift of the intensity lower values (pupil region) of the image to middle intensities which characterizes the iris region. The second border, iris—sclera is characterized by the shift of middle values of intensity to the highest values (sclera region) of the image.

The iris consists of a weave of connective tissues, fibres, rings and colours which constitute a distinctive and unique mark of people when observed from a short distance. Besides, as a visible feature we can see a sinuous structure so-called collarette surrounding the pupil region. Likewise, a cumuli of structural features are visible in the iris which can be classified in two categories (Li and Jain 2009). The first category includes features that relate to the pigmentation of the iris (e.g., pigment spots, pigment frill). The second one refers to the movement-related features, in other words features of the iris relating to its function as pupil size control (e.g.,iris sphincter, contraction furrows, radial furrows). These are a few characteristics which explain why this biometric modality is one of the most reliable ways to identify an individual. Also, its geometric shape (circular or elliptical depending on the point of view) constitutes another feature of great importance for automatic detection.

Iris recognition stages

A conventional iris recognition system consists of the four following stages: image acquisition, preprocessing, feature extraction, and pattern matching. Generally speaking, the process starts with the acquisition of the iris image and concludes with the decision to

Fig. 1 Iris frontal view



accept or reject the claimed identity. Figure 2 shows the flow chart of an iris recognition system. The image acquisition stage aims to capture a sequence of iris images using a special device (e.g., cameras, sensors) which operates in the visible spectrum (380–750 nm) or the near infra-red spectrum (700–900 nm) (Li and Jain 2009; Matey et al. 2006). There are several public image databases available for researching (Bowyer et al. 2008; Li and Jain 2009).

The preprocessing stage involves several steps such as: spoofing detection, image quality assessment, iris segmentation, and normalization. Spoofing detection refers to measurement techniques such as liveness indicators to differentiate the genuine claim from various classes of fake claims (e.g., printed iris images, video playbacks, artificial eyes, patterned contact lenses, and other artifacts) (Chen et al. 2012). The image quality assessment step involves many quality factors such as: defocus blur, motion blur, pupil dilation, pixel-counts, specular reflection, lighting variations, off-angle, eyelashes and eyelid occlusion (Kalka et al. 2010). The earlier these quality factors are detected and corrected, the more accurate the process of iris recognition will tend to be. Many iris recognition systems impose various constraints on the image acquisition process in order to reduce the adverse effects of the quality factors (Rathgeb et al. 2013). Nevertheless, developing less-constraining systems is an ongoing challenge (Proença and Alexandre 2007). The iris segmentation step is based on a sequence of tasks: finding an iris in the image, demarcating its inner and outer boundaries at the pupil and sclera, detecting the upper and lower eyelid boundaries if they occlude and finally detecting and excluding any superimposed eyelashes or reflections from the cornea or eyeglasses (Daugman 2007). In order to get the best results, several techniques have been used such as: Hough transformation (Wildes 1997), integro differential operator (Daugman 2004), active contours (Daugman 2007), pulling and pushing method (He et al. 2009), game theory (Roy et al. 2012), among others. To this end, the iris segmentation process is frequently known as iris localization or iris location (Burge and Bowyer 2013). The last step, the normalization process of the iris region, deals with the problems related to image dimensions. These problems are due to pupil variations, varying imaging distance, camera rotation, eye and head tilt, among others (Daugman 2004). The rubber sheet model is the most frequently used technique for the normalization process (Daugman 2004). However, in order to reduce processing time, some studies have skipped the normalization process (Birgale and Kokare 2010).

In the feature extraction stage, the most discriminant features are obtained from the textural content of the iris. This is based on encoding algorithms which have been developed using various approaches: bank of spatial filters (Ma et al. 2003), 2D Gabor

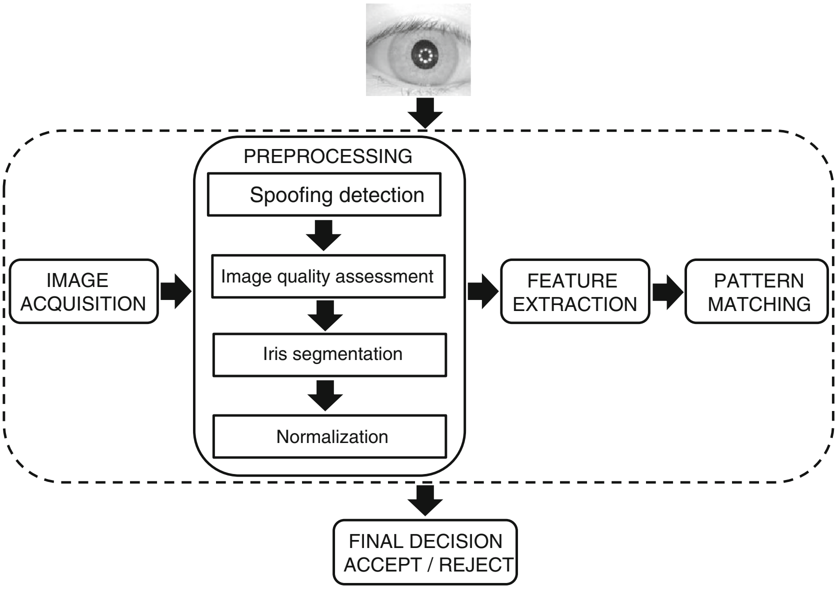


Fig. 2 Iris recognition stages

wavelets (Daugman 2004), discrete cosine transforms (Monro et al. 2007), 2D Discrete Fourier Transforms (Miyazawa et al. 2008), ordinal features (Sun and Tan 2009), multi-scale combined directional wavelet filter bank (Rahulkar and Holambe 2012), among others. The pattern matching stage helps to verify if an entry identity corresponds to any of the enrolled ones in the genuine user database. This is carried out through the use of several similarity measures which are determinant to decide if the claimed identity can be accepted or rejected. Hence, if the entry identity (codified as iris feature vector) and the claimed identity (codified as iris feature vector which has been enrolled earlier) have a degree of similarity (e.g. measured by Hamming distance) lower than the system threshold, then the claim is accepted; otherwise, it is rejected (or vice versa if another dissimilarity measure is used). Various metrics can be used to measure the difference between two iris codes such as: euclidean distance (Sanchez-Avila and Sanchez-Reillo 2002), hamming distance (Daugman 2004), BLPOC function (Miyazawa et al. 2008).

Outstanding companies and active patents on iris recognition

A major advance in the field of iris recognition results from the expiration of two patents (Rathgeb et al. 2013). The first one is the pioneer patent dealing with the general idea of the iris recognition process. It was developed by the ophthalmologists Flom and Safir (1987) and it expired in 2005. The second one, developed by the professor John Daugman (1994), was used to protect the iris-code approach and expired in 2011. From then on, iris recognition has given rise to the creation of new companies and has generated competition in the security market to develop the most reliable products. For instance, Iridian Technologies (now L-1 Identity solutions) was the unique provider of iris recognition technology until the patent by Flom and Safir (1987) fell into public domain in 2005. The company has licensed its technology to several partners for the development of hardware and camera platforms for various applications and environments such as LG Electronics, Oki, Panasonic, Sagem, IrisGuard (UK), Sarnoff, IRIS, Privium (NL), CHILD Project, CanPass, Clear (RT-Registered Traveller), IBM and EyeTicket Corporation. The market has gone through a series of changes and has been characterized by frequent mergers and takeovers. Among such merging, let us mention the agreement between Cross Match technologies and Smith Heimann Biometrics GmbH in 2005; the creation in 2006 of L-1 Identity Solutions merging Viisage, Identix, and Iridian Technologies, followed by the takeover in 2008 of Bioscript and Digimarc; the purchase by Sagem of Motorola biometric business unit in 2009; the purchase in 2009 of Atrua Technologies by AuthenTec, or the takeover of L-1 by Sagem Morpho in 2010 (Sempere 2011).

Although this article falls within the scope of bibliometry, we will provide some brief comments about the industrial use and active patents in the field of iris recognition. Knowing about patents is important because of their role in controlling and protecting the major inventions in the field. Therefore, we have carried out a retrospective search about iris recognition patents in the Derwent Innovations Index (by Thomson-Reuters) database which constitutes the most extensive source of information about patents. According to this source, 760 companies have patented several products based on iris recognition. Table 1 lists the top 20 companies which have produced the highest number of patents. This table provides details such as: the name of the company, record count and percentage of the total amount of companies.

In order to get a detailed and updated information about specific products using iris recognition, we recommend to check the website of the mentioned companies. In addition to this, Table 2 shows the top 20 most cited active patents having as base the previously mentioned retrospective search. In this table, we provide the following details: US patent number, inventor name, company name, patent title, cited times and published date. The US patent number is a good identifier to facilitate the accessibility of patent information.

Methodological approach

Nowadays, two powerful databases control a wide range of refereed information; the WoS (created by Thomson-Reuters) and Scopus (created by Elsevier). From an historical point of view, the WoS has had complete control over citation information for years and therefore provides access to the world leading citation databases. Besides, it includes a multidisciplinary coverage of 12,000 of the highest impact journals worldwide and of over 150,000 conference proceedings, with backfiles up to 1,900. WoS is updated on a weekly basis. However, articles from major journals generally appear within a few weeks of publication. Meanwhile in 2004, Scopus emerged as an interesting alternative tool in the information market. Scopus has a scope of approximately 19,500 peer-reviewed journals and more than 3.2 million conference proceedings, going back as far as 1823. The database is intended to be updated daily as well. Scopus represents now the largest database for multidisciplinary peer-reviewed literature and hence is best suited as a base to assess the current progress in the field of iris recognition. This is corroborated by many previous studies aiming to compare the scope of information covered by WOS versus Scopus (de Moya-Anegn et al. 2007; Meho and Yang 2007; Meho and Rogers 2008). Therefore, we opted for Scopus as the source of publication records in our bibliometric analysis.

Our study includes a retrospective search on Scopus from the most relevant papers produced on iris recognition in the period 2000–2012 and published in English. The research was performed using the executed query TITLE-ABS-KEY(“iris recognition”)

Table 1 The top 20 companies with more patents

Company	Record count	Percentage
1. LG ELECTRONICS INC	67	8.82
2. OKI ELECTRIC IND CO LTD	65	8.55
3. HONEYWELL INT INC	22	2.89
4. IRITECH INC	15	1.97
5. MATSUSHITA DENKI SANGYO KK	15	1.97
6. TOSHIBA KK	11	1.45
7. AMERICAN EXPRESS TRAVEL RELATED SERVICES	10	1.32
8. BIZMODELINE CO LTD	9	1.18
9. EVER MEDIA CO LTD	9	1.18
10. GLOBAL RAINMAKERS INC	8	1.05
11. SAMSUNG ELECTRONICS CO LTD	8	1.05
12. UNIV YONSEI IND ACADEMIC COOP FOUND	8	1.05
13. CANON KK	7	0.92
14. INT BUSINESS MACHINES CORP	7	0.92
15. IRIDIAN TECHNOLOGIES INC	7	0.92
16. SARNOFF CORP	7	0.92
17. ELECTRONICS&TELECOM RES INST	6	0.79
18. EYELOCK INC	6	0.79
19. IRISCAN INC	6	0.79
20. SAMSUNG DIGITAL IMAGING CO LTD	6	0.79

AND PUBYEAR $>$ 1999 AND PUBYEAR $<$ 2013 AND LANGUAGE(“English”). We were able to retrieve 1,405 documents from nine different document sources[1]. The distribution of papers per document types is as follows: Conference Paper (969; 71.57 %), Article (331; 24.45 %), Conference Review (48; 3.55 %), Review (27; 1.99 %), Note (10; 0.74 %), Article in Press (10; 0.74 %), Short Survey (5; 0.37 %), Erratum (3; 0.22 %) and Letter (2; 0.15 %). From these data, we discarded the papers classified as Conference Review (48; 3.55 %) and Erratum (3; 0.22 %) because of their lack of relevance to the bibliometric analysis. We selected 1,354 documents to extract the information relevant to examine the current progress in the field of iris recognition.

A process of normalization was carried out to standardize the name of the authors recovered in the selected publication records. In some cases, the author’s names are duplicated with a slight difference. Therefore, we developed a semi-automatic process in order to disambiguate the authors’ names when their similarity could lead to confusion. First, we made up an alphabetical list of the authors’ names using the software Calc[2]. Each item of the list includes a list of identifiers corresponding to each publication record of the author. Then, we looked manually for duplicates in the whole list of author’s names . Thus, the well-known authors are fused directly from the list. When the authors’ name is not well-known, we correlated two attributes: authors’ address and country from their respective publication records. In case the previous procedure failed to resolve ambiguities,

[1] A list of all document sources can be found on the Scopus website (www.scopus.com)

[2] The installer and documentation can be found on the Calc website (http://www.openoffice.org/product/calc.html)

Table 2 The top 20 most cited active patents sorted by number of times are cited

US patent#	Inventor	Company	Tittle	Cited#	Presented
1. US2006050933-A1	H. Neven, A. Hartwig, H. Adam	NEVENGINEERING INC	Face recognition method for identifying individual, involves calculating similarity score between single image and reference image based on facial feature comparison and iris feature comparison	73	06/21/2005
2. US6377699-B1	C. Musgrave, J. L. Cambier	IRISCAN INC, IRIDIAN TECHNOLOGIES INC	Telephone security module for unlocking telecommunication device, compares stored template of image of iris of person's eye with iris image obtained by camera to identify the person	59	05/12/1999
3. US6526160-B1	H. Ito	MEDIA TECHNOLOGY CORP, MEDIA TECHNOLOGY KK	Iris information sensor capable of remarkably reducing time required from image pickup of iris image to generation of iris code as well as of simplifying system	55	07/09/1999
4. US5956122-A	R. Doster	LITTON SYSTEMS INC	Human iris direction determining method for identification purpose	53	06/26/1998
5. US6505193-B1	C. Musgrave, J. L. Cambier	IRIDIAN TECHNOLOGIES, IRIDIAN TECHNOLOGIES INC	System for biometric database searching for identification of person at computing platform has template comprising digital certificate and obtained biometric image	48	12/1/1999
6. US6594377-B1	B. C. Kim, J. J. Chae	LG ELECTRONICS INC	Iris recognition system for automatic access control systems, has optical imager obtaining iris image, concave outer casing supporting inner case that surrounds imager and hinge bracket that enables rotation of inner case	42	1/11/1999
7. US8186830-B2	U. Grotehusmann, G. Youseffi, G. Youssefi	BAUSCH&LOMB INC	Iris pattern recognition and alignment for aligning diagnostic and therapeutic iris images uses limbal edge detection to provide pupil center translation information	38	05/10/2001
8. US6546121-B1	T. Oda	OKI ELECTRIC IND CO LTD	Iris recognition procedure for individual identification - involves extracting data of iris area positioned on standard linearity and comparing with registered data	34	03/05/1999
9. US6542624-B1	T. Oda	OKI ELECTRIC IND CO LTD	Iris code generator used in individual identification has controller which judges whether eye of user is real to imitative based on evoked biological reaction	32	07/16/1999

Table 2 continued

US patent#	Inventor	Company	Tittle	Cited#	Presented
10. US2002130961-A1	W. H. Lee, A. K. Yang, J. J. Chae	LG ELECTRONICS INC, KINSEISHA KK	Display device for iris recognition system, displays distance and moving direction of user based on distance between user and iris recognition camera	29	03/14/2002
11. US2002131622-A1	W. H. Lee, A. K. Yang, J. J. Chae	LG ELECTRONICS INC, KINSEISHA KK	Focus position adjusting method in iris recognition system, involves measuring distance between user and camera, by analyzing characteristics of projected image extracted from user images	29	03/14/2002
12. US2005084137-A1	D. Kim, B. Choi, S. Paik	IRITECH INC	Iris identification system for individual identification has iris recognition cameras that photograph irises of person using stereoscopic face information created according to photographed face images of person	28	10/17/2008
13. US2007036397-A1	R. Hamza, R. M. Hamza	HONEYWELL INT INC	Iris recognition method for personnel identification, involves using border of pupil for segmenting iris	26	01/26/2006
14. US6760467-B1	S. G. Min, J. J. Chae	KINSEISHA KK, LG ELECTRONICS INC	Iris recognition method to prevent illegal access of image, involves checking appearance of illuminated LED images in photographed message image to judge authenticity with LEDs being provided near camera	25	03/21/2000
15. US2007047772-A1	J. R. Matey, J. R. Bergen	SARNOFF CORP	Iris image identifying method for tracking identity of e.g. cat, involves obtaining iris image of eye, generating original iris template from iris image, and generating modified iris template by extracting portion of iris template	24	08/25/2006
16. US2002154794-A1	S. Cho, S. W. Cho	EVERMEDIA CO LTD	Non-contact human iris recognition by comparing image pixel information for inner boundaries of iris for conversion of region into polar coordinates	23	12/07/2001
17. US2007091264-A1	K. Bjoern, K. Bjorn, B. Kahlen	BAUSCH&LOMB INC	Patient eye data acquisition system for laser eye surgery, has iris recognition unit for obtaining iris code of eye of patient	22	03/31/2004

Table 2 continued

US patent#	Inventor	Company	Tittle	Cited#	Presented
18. US2002150281-A1	S. Cho, S. W. Cho	EVERMEDIA CO LTD	Recognizing method for a human iris using Daubechies wavelet transform extracting characteristic values of characteristic vector from extracted image including high frequency components	22	09/05/2001
19. US2004164848-A1	E. Hwang, J. Lee, U. H. Hwang	SAMSUNG ELECTRONICS CO LTD	User authentication method for use in door lock/unlock system, involves finding authenticated biometric with registered biometrics and threshold values that are set depending on matching of input password with registered password	22	01/21/2004
20. US2006165266-A1	R. M. Hamza, R. Hamza	HONEYWELL INT INC	Human eye‘s iris recognition method for use in e.g. passport control, involves acquiring image of eye, and approximating center of pupil, and using center of pupil as origin of polar coordinate system	21	01/26/2005

we retrieved additional information from the INTERNET in order to clear any doubts. This process may seem a bit tedious but it is important to get the most accurate picture of who are the researchers in the field.

Our bibliometric study takes into account six main issues and is developed through histogram graphs, collaboration networks, SOM and tables. The first issue is the temporal evolution of iris recognition which is based on paper production by each year in the period under study. In the leading authors issue, we give a ranking of the most productive authors, the most cited authors, the leading authors with more impact in the field and the collaboration network of the most productive authors. The identification of the leading authors with more impact in the field is very important to identify the most relevant bibliographical sources because of the most productive and most cited ranks are not conclusive. To establish the ranking of the most productive authors, we take into account their number of publications (scientific output). We identified the most cited authors according to the number of times they are cited by other researchers. The leading authors with more impact in the field are identified using two elements: quality of scientific output and leadership. In order to assess the quality of the scientific output of the leading authors, two indices are sufficient: the h-index (measure of productivity) and the a-index (measure of impact) (Bornmann and Hans-Dieter 2009). The *h*-index is a novel bibliometric index proposed by the physicist researcher Jorge Hirsch (2005). This index tries to quantify the impact of an individual scientist and to overcome some deficiencies among traditional citation counting and ranking methods. The *h*-index is based on the premise that a scientist has an index *h* if *h* of his or her papers has at least h citations each. For example, a scientist with an *h*-index of ten has published ten works, each being cited at least ten times. In this work, we calculate two values of *h*-index for each leading author. A first value refers to the *h*-index taking into account all the author's papers which are indexed in Scopus. The other value in brackets represents the *h*-index including only the papers recovered in the query executed for this study. The analysis of these two values could be useful to indicate the degree of specialization of the authors in the field. As for the *a*-index, it is estimated according to the average number of citations of publications used in the Hirsch core (Jin 2006).

In addition, we measured the author's leadership thanks to three indicators: research guarantor approach (Moya-Anegn et al. 2013), excellence indicator (Bornmann et al. 2012) and a combination of both for each leading author. These indicators are suitable to assess an individual author in spite of the fact they have been originally proposed to rank institutions and countries. The research guarantor is assigned a special status in the research team. He is in charge of assigning the authorship's degree; he approves the protocols to be followed in the study; he supervises manuscript's correction, proof reading and takes care of the correspondence when the paper is submitted. In practice, the identification of the research guarantor is not easy. Therefore it is always assumed that the research group to which the corresponding author belongs is the research guarantor (Moya-Anegn et al. 2013). As for the research guarantor's measurement, we rely on the number of times an author signs a paper using the same affiliation as the research guarantor. Regarding to the excellence indicator, let us mention that papers classified among the 10 % most cited papers belong to the excellence category (Bornmann et al. 2012). For each leading author, we calculate the percentage of papers in the excellence category. The last indicator measures the percentage of papers for which the author is identified as the research guarantor when the paper is in the excellence category.

From the collaboration network, we obtained centrality measures which help to describe the collaboration pattern of the top 20 most productive authors. The centrality measures indicates how central is the role of an author in a collaboration network. This shows to what extent the author is connected to the others (Yan et al. 2010). In this work, we have used three centrality measures: betweenness, closeness and degree (Yan et al. 2010). Betweenness centrality measures the number of shortest paths based on the geodesic distance between each author and all the other ones who connect through him. This reflects the capacity of an author to participate in several research networks. The closeness centrality stands for the distance between an author and all the other ones in the network using the geodesic distance. A high closeness centrality means that the author is very efficient when he or she collaborates with the others in the network. The last measure is the degree centrality which calculates the number of direct relationships of an author within the network. These centrality measures enable us to assess interaction and collaboration patterns.

As a third issue, we provide a ranking of the most cited papers. The significant conventions issue includes a selection of the conventions with the highest number of publications in the field of iris recognition. Meanwhile, the leading journals issue gives a list of the journals with the highest impact which include publications related to the field. The last issue deals with research topics that have been addressed between 2000 and 2012 and provides a comprehensive description of the most significant topics on iris recognition. The analysis of this 6th issue will enable us to obtain a quantitative assessment of the current progress and trends in the field of iris recognition. Similar assessments have been developed previously aiming at similar objectives through extracting information from co-citation analysis (Natale et al. 2012; Shiau and Dwivedi 2013; Slyder et al. 2011). However, these studies are difficult to replicate and rely on unpublished weighting values of a different nature from ours.

Our proposal relies on a more simple and effective method to identify topics as of current interest from a research perspective. These topics are identified based on the respective keywords found in the papers published in the field of iris recognition during the period under study. To this end, starting with the keywords of the recovered publication records, we obtained the most relevant keywords by fusing the related keywords and by matching them with the number of publications. These operations are completed in a semi-automatic fashion. Using the software Calc, the keywords have been ordered in alphabetical order. Then, they have been fused manually. Thus the final ordering of the keywords according to the respective number of publications provides the ranking of the outstanding research topics. These topics have been classified into three main categories: ongoing, emerging, and decreasing according to their corresponding number of publications over the period under study. To a certain extent, these three categories reflect the level of interest of the researchers, as well as other factors (e.g. available funds for planned research, background knowledge and familiarity with the topic and its related research, availability of research staff and equipment and so on). The first two categories: ongoing and emerging are based on whether the slope value of the fitted linear model of the production by year is positive. In addition to this constraint, the emerging category includes articles published only in the second half of the period under study. In general, these two categories include research topics which may be new or which deal with a challenging and enduring problem difficult to solve. Therefore they are promising research venues in terms of future publications. The decreasing category refers to research topics which are characterized by a negative slope of the fitted linear model of the production by year. This category might include topics which are not worth pursuing because there are alternative solutions to the problem they raise or, as in the majority of cases, the problem has been solved.

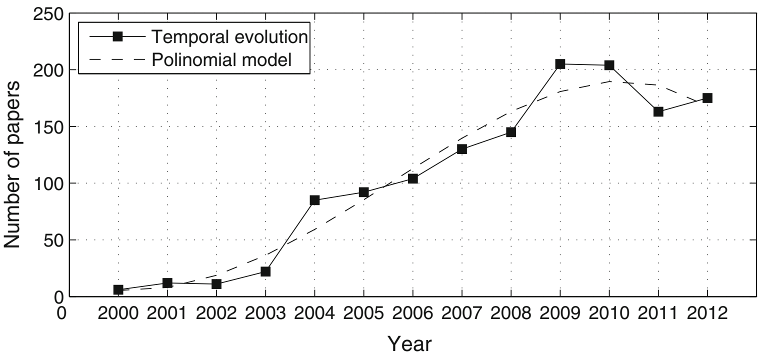


Fig. 3 Temporal evolution

At the end of the outstanding research topics section, we have obtained a multidimensional report by matching six selected research topics with the most cited authors. This has been carried out using the SOM theory also known as Kohonen maps (Kohonen 1995) which enables to visualize the distribution of the publications of the most cited authors for each analyzed research topic. The Kohonen maps are artificial neural networks (ANN) which adapt themselves to the input signals based on the Kohonen algorithm. In this way, we can derive the most relevant research topics on iris recognition and the respective leading authors. As input to the SOM method, we must design a matrix whose rows represent the authors while the respective columns represent the research topics; each match corresponds to the co-occurrence quantity. The output layer consists of a network of neurons or nodes which are typically arranged as a 2D vectors. The nodes are connected to their neighbours according to either a square or hexagonal neighbourhood set-up. The resultant map can be interpreted as clusters where the input data with similar characteristics will form adjacent zones. For example, the proximity of each element is shown by means of clusters with different colour tones which are meant to represent the productivity level of the most cited authors. The clusters in red represent the most productive authors whereas the clusters in blue indicate the authors with the least number of publications. For the creation and visualization of the SOM, we used a demo distribution of Viscovery SOMine[3] software.

Results and discussions

Temporal evolution

As mentioned in the previous section, we used 1,354 publication records between 2000 and 2012 to assess the current progress of iris recognition research. The temporal evolution of the number of publications in the field appears in Fig. 3. This graph shows a solid and incremental volume of work in the field. In the period 2000–2003, the paper production was conservative. A notable increase is observed between 2004 and 2009. From 2009 to

[3] The installer and documentation can be found on the Viscovery SOMine website (http://www.viscovery.net)

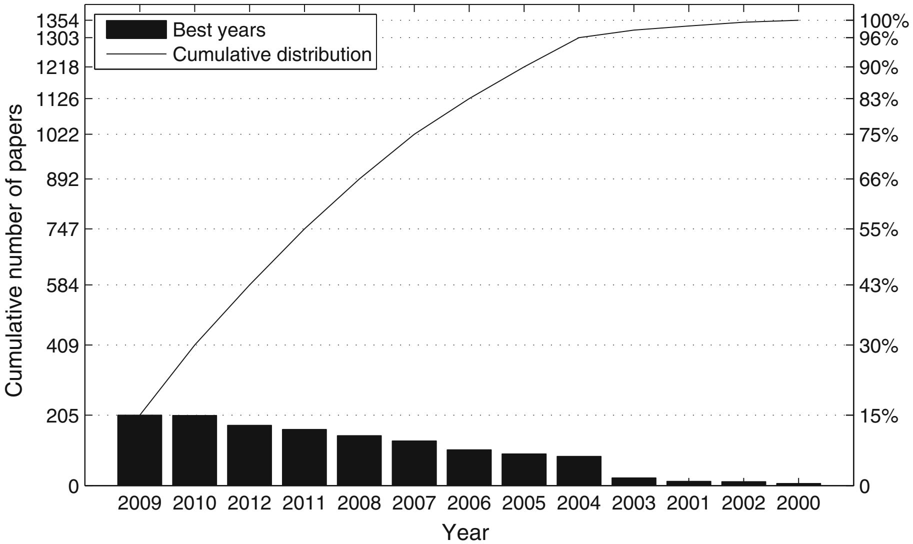


Fig. 4 Cumulative distribution of paper production

2012, we observe a slight tail off. The temporal evolution for the entire period stands for a fitted polynomial model of fourth degree (see Fig. 3).

Another way to show the temporal evolution is depicted in Fig. 4. In this figure, the yearly publications are ordered in a decreasing fashion and a cumulative distribution is presented to show the percentage of the cumulative production by year in comparison with the total production (TP). Thus, we notice that the production in the periods 2008–2012 and 2004–2012 represents respectively 66 and 96 % of the total article production. Besides, this graph indicates that the crucial increase of iris recognition studies starts in 2004.

Leading authors

The analysed publication records list the papers of 1960 authors, among whom 365 (18.62 %) have produced three or more publications. Meanwhile, the top 100 (5.10 %) most productive ones have published six or more articles. Table 3 shows in a detailed way the information concerning the top 20 most productive authors. For each author, we provide name, TP, total collaborations (TC) in terms of TP, total references to other papers (TREF), average of the total references (TREF/TP) and the order in the ranking of the top 20 most cited authors (TMC). This last feature is an alternative way to show which ones among the most productive researchers are the most cited taking into account the number of times their articles are cited by others.

The most cited authors are the ones whose names appear the most frequently in the references of the papers recovered by the query executed in this work. For example, 1,109 (56.58 %) authors are cited at least once. The top 100 most cited authors are cited at least 40 times. The top 20 most cited are cited at least 158 times (see Table 4 for further details). For each author, we mention name, number of times the author is cited (NTC), number of times their published work during 2000–2012 has been cited (NTCP), total production

Table 3 The top 20 most productive authors sorted by the number of publications

Author	TP	TC	TREF	TREF/TP	TMC
1. T. Tan	51	51	961	18.84	2
2. K. R. Park	44	38	924	21.00	–
3. Z. Sun	41	41	735	17.93	8
4. Y. Du	32	30	721	22.53	12
5. R. W. Ives	30	30	461	15.37	–
6. A. Uhl	29	29	420	14.48	–
7. K. Roy	25	25	445	17.80	–
8. P. Bhattacharya	25	25	445	17.80	–
9. H. Proença	24	17	506	21.08	17
10. K. W. Bowyer	21	19	385	18.33	10
11. P. J. Flynn	21	21	390	18.57	9
12. M. Xie	18	18	197	10.94	–
13. Y. Wang	17	17	435	25.59	5
14. J. Kim	17	17	250	14.71	16
15. A. Ross	17	16	301	17.71	11
16. B. J. Kang	16	16	416	26.00	–
17. C. Belcher	15	15	415	27.67	–
18. M. Savvides	15	15	224	14.93	–
19. P. Shi	15	15	231	15.40	–
20. J. Daugman	13	3	201	15.46	1

(TP), total collaborations (TC) in terms of total production and the ranking order in the top 20 most productive authors (TMP).

Table 5 lists the leading authors with more impact with their corresponding indicators of quality of scientific output and leadership. Thus, for each author, we specify: name, *a*-index, *h*-index, specialized *h*-index (s. *h*-index), percentage of total production as research guarantor (Gtr), percentage of total production as excellent papers (Exc), percentage of papers for which the author is identified as the research guarantor when the paper is in the excellence category (GE). These authors have been listed in descending order by GE and later by the *a*-index indicator. Maximum values for every cathegory are in bold.

As we can see in Table 5, T. Tan is the author with the highest value in all indexes except the *a*-index. On the *a*-index he is only surpassed by Y.Wang and J.Daugman. The reason for this is that T. Tan has less impact than Y. Wang and J. Daugman since his works are cited less. This is compensated by a higher number of works on the excellency cathegory. Therefore, on 'iris recognition' the selection of the leader will depend on the criteria used. On the other hand we have to mention that the authors with the highest leadership are always their 'guarantors'. The authors with a high *a*-index value generally obtains high values on the *h*-index and on the leadership indicators as well. So, they receive a high number of cites in the publications that are used to obtain their *h*-index.

Besides, we think that in order to be considered very specialized, an author should have a specialized *h*-index higher than the 60 % of the general *h*-index. Moreover, taking together, the *a*-index and the *h*-index can discriminate the quality of the scientific output of these authors. We consider specialization in respect to iris recognition, but if the topic is extented to a wider discipline such as biometry then the specialization of the considered

Table 4 The top 20 most cited authors sorted by total of cited times

Author	NTC	NTCP	TP	TC	TMP
1. J. Daugman	2,367	1,696	13	3	20
2. T. Tan	1,639	1,246	51	51	1
3. L. Ma	1,063	850	9	9	–
4. D. Zhang	796	651	7	7	–
5. Y. Wang	686	534	17	17	13
6. A. Jain	670	43	3	3	–
7. R. Wildes	528	23	1	1	–
8. Z. Sun	443	400	41	41	3
9. P. J. Flynn	440	247	21	21	11
10. K. W. Bowyer	432	248	21	19	10
11. A. Ross	415	109	17	16	15
12. Y. Du	302	186	32	30	4
13. J. R. Matey	263	68	7	7	–
14. K. Hollingsworth	241	162	9	9	–
15. J. Cui	238	128	11	11	–
16. J. Kim	218	148	17	17	14
17. H. Proença	216	101	24	17	9
18. N. A. Schmid	211	149	12	12	–
19. R. Sanchez-Reillo	171	72	10	9	–
20. C. Sanchez-Avila	158	71	8	8	–

authors would be higher. Among the authors with the highest quality of scientific output in which the *a*-index and *h*-index are combined, let us mention: J. Daugman, Y. Wang, T. Tan and K. W. Bowyer.

With respect to the leadership indicators, we would like to underline that out of the 1,354 analyzed papers, only 619 have at least one citation. From this base, we observe that the top 10 % most cited papers are those which are cited at least 17 times. From this, we can remark the authors who are research guarantors more than 90 % of the times and who have published only excellent papers as research guarantors. This is the case of the following researchers in decreasing order of leadership: J. Daugman, T. Tan, J. Cui, H. Proença and Y. Du. A lower degree of leadership applies in the case of the authors with only excellence papers as research guarantors, whatever the percentage of times they have acted as research guarantors. In this category, let us mention: Y. Wang, K. W. Bowyer, P. J. Flynn and Z. Sun.

As concerns the pattern of collaboration, Fig. 5 shows the collaboration network of the top 20 most productive authors developed in NetDraw[4]. In that network, the filled squares in blue stand for the top 20 most productive authors and the filled circles in red represent their respective partners. In order to get a clearer picture of the network, we selected the ranking of the top 100 most productive authors who have at least two collaborations with the top 20 most productive authors. Therefore, we observe that the highly ranked authors cooperate more frequently, forming 4 noticeable collaboration clusters. The first one corresponds to the core authors K. R. Park, B. J. Kang and J. Kim, who make up the biggest

[4] The installer and documentation can be found on the NetDraw website (www.analytictech.com)

Table 5 The leading authors with more impact in the field considered by GE and then by *a*-index

Author	*a*-index	*h*-index(s. *h*-index)	Gtr	Exc	GE
1. T. Tan	72	**39 (16)**	**47**	**15**	**15**
2. Y. Wang	89	18 (11)	18	9	9
3. Z. Sun	26	12 (12)	36	9	9
4. J. Daugman	**211**	13 (8)	12	7	7
5. J. Cui	29	8 (8)	11	6	6
6. L. Ma	141	7 (6)	8	5	5
7. Y. Du	16	12 (8)	30	3	3
8. K. W. Bowyer	29	32 (8)	18	2	2
9. P. J. Flynn	29	20 (8)	17	2	2
10. C. Sanchez-Avila	23	8 (3)	4	3	2
11. R. Sanchez-Reillo	22	8 (3)	9	3	2
12. J. Kim	20	7 (6)	12	2	2
13. K. Hollingsworth	39	6 (4)	9	1	1
14. J. R. Matey	32	5 (2)	7	1	1
15. N. A. Schmid	19	10 (7)	11	2	1
16. K. R. Park	17	15 (9)	27	3	2
17. R. W. Ives	17	9 (8)	25	3	2
18. H. Proença	17	8 (5)	24	1	1
19. B. J. Kang	17	10 (6)	3	3	1
20. A. Ross	15	20 (6)	13	2	1
21. M. Savvides	15	11 (3)	13	1	1
22. C. Belcher	11	6 (6)	13	1	1
23. P. Shi	9	6 (3)	11	0	0
24. A. Uhl	6	13 (2)	20	0	0
25. M. Xie	5	4 (2)	17	0	0
26. K. Roy	4	5 (3)	25	0	0
27. P. Bhattacharya	4	12 (3)	16	0	0

Bold values signifies the maximum value for each column

cluster with 147 collaborations. They are followed by the core authors T. Tan, Z. Sun and Y. Wang with 136 collaborations. The third notable cluster is formed by P. J. Flynn, K. W. Bowyer, M. Savvides and A. Ross, with 127 collaborations. The fourth notable cluster is formed by Y. Du, R. W. Ives and C. Belcher, with 107 collaborations. Let us mention that only J. Daugman is less prone to collaborate with other authors. This is corroborated by Table 3 where J. Daugman shows only 3 collaborations for a total of 13 papers. Most of the trends in collaborations are influenced by academic interest. Table 6 shows the affiliation for every author considered along this work.

Table 7 shows the list of the centrality values of the top 20 most productive authors in descending order according to the betweenness measure. For each of the most productive authors, Table 7 mentions: name, betweenness centrality, closeness centrality and degree centrality. Likewise, in this Table we can observe a high degree of correspondence of the centrality measures among the authors. This means that overall, authors with high betweenness centrality also have high closeness centrality and high degree centrality. We observe that M. Savvides has a high betweenness and low values of closeness and degree.

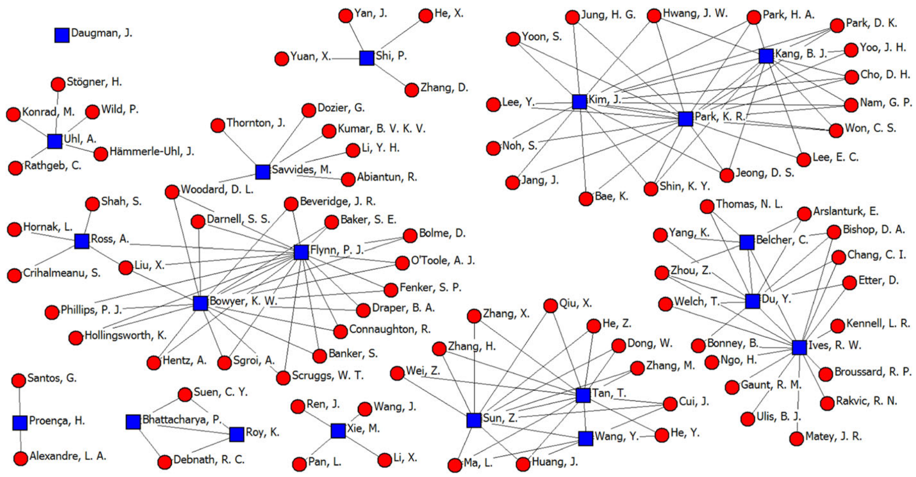


Fig. 5 Collaboration network of the top 20 most productive authors

This is due to the fact that the author has a key position which connects a few networks of researchers despite his lack of substantial direct connections.

Most cited papers

The ranking of the top 20 most cited papers is another criterion in the evaluation of a research field. Table 8 shows the ranking of the top 20 most cited papers. For each paper, the table specifies title, author's name, publication year, source title and number of cited times. Concerning this last attribute, two values are shown. The first one is the number of cited times for all papers in Scopus; the other one in brackets indicates the number of times it is cited in the papers recovered in our study. The analysis of these two values for each paper helps to establish the citations ranking as well as the impact of the paper.

In this way, we observe that the first six most cited papers belong to authors who are among the most cited ones. Besides, these papers have been published in journals of high impact as shown in "Leading journals" section. The top 20 most cited papers cover at least a period of 3 years. This is approximately the length of time required for a publication to get enough recognition to be ranked among the most cited journals. Moreover, it is important to mention that J. Daugman holds a good position in the field of iris recognition since six of his papers appear in this ranking, which represents 30 % of the total amount of papers.

Significant conventions

The significant conventions issue includes congresses, conferences and workshops dealing mostly with iris recognition. From the publication records in our study, we recovered information about 986 papers classified as Conference proceedings and Serials. Our analysis is based on 500 distinct conventions. Table 9 provides the ranking of the top 20 most productive conventions on iris recognition. The table includes convention acronym, convention name, TP, percentage of total production (TP %) in comparison with the total number of convention papers for the analysed period. We observe that iris recognition is

Table 6 Authors and their affiliations.

Author	Affiliation
P. Bhattacharya	Department of Computer Science, University of Cincinnati, United States
C. Belcher	Department of Electrical and Computer Engineering, Indiana University-Purdue University, United States
K. W. Bowyer	Department of Computer Science and Engineering, University of Notre Dame, United States
J. Cui	National Laboratory of Pattern Recognition, Institute of Automation, China
J. Daugman	Computer Laboratory, University of Cambridge, United Kingdom
Y. Du	Department of Electrical and Computer Engineering, Indiana University-Purdue University, United States
P. J. Flynn	Department of Computer Science and Engineering, University of Notre Dame, United States
K. Hollingsworth	Department of Computer Science and Engineering, University of Notre Dame, United States
R. W. Ives	Electrical and Computer Engineering Department, United States Naval Academy, United States
A. Jain	Department of Computer Science and Engineering, Michigan State University, United States
B. J. Kang	Technical Research Institute, Hyundai Mobis, South Korea
J. Kim	Department of Electrical and Electronic Engineering, Yonsei University, South Korea
L. Ma	National Laboratory of Pattern Recognition, Institute of Automation, China
J. R. Matey	Center for Biometric Signal Processing, United States Naval Academy, United States
K. R. Park	Division of Electronics and Electrical Engineering, Dongguk University, South Korea
H. Proença	Department of Computer Science, University of Beira Interior, Portugal
A. Ross	Lane Department of Computer Science and Electrical Engineering, West Virginia University, United States
K. Roy	Department of Computer Science and Software Engineering, Concordia University, Canada
C. Sanchez-Avila	Department of Applied Mathematics, E.T.S.I. Telecommunication, Polytechnic University of Madrid, Spain
R. Sanchez-Reillo	Group for Identification Technologies, Carlos III University of Madrid, Spain
M. Savvides	Cylab Biometrics Center, Carnegie Mellon University, United States
N. A. Schmid	Lane Department of Computer Science and Electrical Engineering, West Virginia University, United States
P. Shi	Institute of Image Processing and Pattern Recognition, Shanghai Jiao Tong University, China
Z. Sun	National Laboratory of Pattern Recognition, Institute of Automation, China
T. Tan	National Laboratory of Pattern Recognition, Institute of Automation, China
A. Uhl	Department of Computer Sciences, University of Salzburg, Austria

Table 6 continued

Author	Affiliation
Y. Wang	National Laboratory of Pattern Recognition, Institute of Automation, China
R. Wildes	Sarnoff Corporation, United States
M. Xie	College of Electronic Engineering, University of Electronic Science and Technology, China
D. Zhang	Biometric Research Centre, Hong Kong Polytechnic University, Hong Kong

not the central topic in any recovered convention, but only one of many subjects. This analysis constitutes an important strategy to identify the most prestigious conventions dealing with iris recognition.

Among the most productive authors with the highest number of papers in the significant conventions, let us mention T. Tan, Z. Sun, Y. Du, P. J. Flynn and M. Savvides with three papers each, followed by A. Uhl and K. W. Bowyer with two papers for each of them. The most cited authors with the highest number of papers in the significant conventions are T. Tan, Z. Sun, Y. Du, P. J. Flynn with three papers respectively, followed by K. W. Bowyer and A. Jain, each one with two papers. The top three most significant conventions with the highest number of publications by the most productive researchers are: the "IEEE International Conference on Image Processing" and "Chinese Conference on Biometric Recognition", each one including four papers, followed by the "Mobile Multimedia/Image Processing, Security, and Applications" with three papers. The top three most significant conventions with the highest level of participation by the most cited authors are "IEEE International Conference on Image Processing" and "Chinese Conference on Biometric Recognition", each one with four papers, followed by the "International Conference on Audio- and Video-Based Biometric Person Authentication" with three papers.

Leading journals

From the survey of the publication records, we collected a total of 368 papers corresponding to journal articles. These papers are published in 146 journals. Table 10 lists the top 20 leading journals in the ranking, taking into account the SCImago journal rank indicator (SJR).[5] This ranking includes only the journals with more than two papers on iris recognition. This enables us to identify the most relevant and significant journals. Table 10 includes a bibliographic record for each journal: Print-ISSN, journal name, SJR indicator (year 2013), journal citation report impact factor (JCR year 2012),[6] TP and total production percentage (TP%) out of the total number of journal papers. The indicators SJR and JCR help to assess the quality of scientific journals. The SJR is an open access resource based on Scopus data and is provided by the SCImago research group. Meanwhile, the JCR indicator is a paid resource based on Web of Science data supplied by Thomson-Reuters in

[5] The SJR of each journal indexed by Scopus may be checked in http://www.scimagojr.com

[6] The JCR of each journal indexed by WOS may be checked in http://thomsonreuters.com/thomson-reuters-web-of-science/

Table 7 Centrality values of the top 20 most productive authors

Author	Betweenness	Closeness	Degree
1. P. J. Flynn	191.00	17.00	18
2. M. Savvides	120.00	6.00	6
3. R. W. Ives	107.33	16.50	15
4. K. W. Bowyer	105.00	17.00	17
5. A. Ross	75.00	13.00	5
6. K. R. Park	65.33	18.00	18
7. J. Kim	43.83	17.00	16
8. Y. Du	37.83	14.50	11
9. T. Tan	34.50	13.00	13
10. Z. Sun	25.50	12.50	12
11. B. J. Kang	18.83	15.00	12
12. C. Belcher	16.83	12.50	7
13. A. Uhl	10.00	5.00	5
14. Y. Wang	6.00	9.50	3
15. M. Xie	6.00	4.00	4
16. P. Shi	6.00	4.00	4
17. H. Proença	1.00	2.00	2
18. K. Roy	0.50	3.00	3
19. P. Bhattacharya	0.50	3.00	3
20. J. Daugman	0	0	0

the journal citation report. As we observed previously in the case of significant conventions, there is a noticeable lack of journals specialized in iris recognition research. There are very few papers dealing exclusively with the topic when we consider the global content of the journals.

According to our observations, the most productive authors with the highest number of papers in the leading journals are T. Tan and J. Daugman, each one with three papers, followed by Y. Du, R. W. Ives, Y. Wang, P. Shi with two papers respectively. The most cited authors with the highest number of papers in the leading journals are D. Zhang with five papers, T. Tan and J. Daugman, each one with three papers, followed by Y. Du, Y. Wang and L. Ma with two papers respectively. Besides, the top three journals with the greatest amount of papers by the most productive authors are “Optical Engineering” with four papers, followed by “Computer Vision and Image Understanding” and the journal “Signal Processing” with three papers each. The top three journals with the highest number of papers by the most cited authors are “IEEE Transactions on Pattern Analysis and Machine Intelligence”, “Computer Vision and Image Understanding” and “IEEE Transactions on Image Processing” with four papers respectively.

Outstanding research topics

We conducted an analysis of the research topics dealt with the papers recovered in the query executed for this study. Thus, Table 11 indicates the top 20 outstanding research topics. For each topic reported, Table 11 mentions topic name, yearly article production of the period under study, total production (TP), percentage of total production (TP%) in

Table 8 The top 20 most cited papers

Paper title	Author(s)	Year	Source title	Cited times
1. How Iris Recognition Works	J. Daugman	2004	IEEE Transactions on Circuits and Systems for Video Technology 14 (1), pp. 21–30	917 (498)
2. Personal Identification Based on Iris Texture Analysis	L. Ma, T. Tan, Y. Wang, D. Zhang	2003	IEEE Transactions on Pattern Analysis and Machine Intelligence 25 (12), pp. 1519–1533	496 (301)
3. Efficient iris recognition by characterizing key local variations	L. Ma, T. Tan, Y. Wang, D. Zhang	2004	IEEE Transactions on Image Processing 13 (6), pp. 739–750	418 (267)
4. The importance of being random: Statistical principles of iris recognition	J. Daugman	2003	Pattern Recognition 36 (2), pp. 279–291	365 (158)
5. New methods in iris recognition	J. Daugman	2007	IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics 37 (5), pp. 1167–1175	262 (166)
6. Image understanding for iris biometrics: A survey	K.W. Bowyer, K. Hollingsworth, P.J. Flynn	2008	Computer Vision and Image Understanding 110 (2), pp. 281–307	211 (115)
7. Efficient iris recognition through improvement of feature vector and classifier	S. Lim, K. Lee, O. Byeon, T. Kim	2001	ETRI Journal 23 (2), pp. 61–70	206 (141)
8. Statistical richness of visual phase information: Update on recognizing persons by iris patterns	J. Daugman	2001	International Journal of Computer Vision 45 (1), pp. 25–38	189 (96)
9. Probing the uniqueness and randomness of iriscodes: Results from 200 billion iris pair comparisons	J. Daugman	2006	Proceedings of the IEEE 94 (11), pp. 1927–1934	157 (65)
10. Iris recognition using circular symmetric filters	L. Ma, Y. Wang, T. Tan	2002	International Conference on Pattern Recognition 16 (2), pp. 414–417	141 (135)
11. Local intensity variation analysis for iris recognition	L. Ma, T. Tan, Y. Wang, D. Zhang	2004	Pattern Recognition 37 (6), pp. 1287–1298	131 (76)
12. DCT-based iris recognition	D.M. Monro, S. Rakshit, D. Zhang	2007	IEEE Transactions on Pattern Analysis and Machine Intelligence 29 (4), pp. 586–595	118 (86)

Table 8 continued

Paper title	Author(s)	Year	Source title	Cited times
13. Iris on the move: Acquisition of images for iris recognition in less constrained environments	J.R. Matey, O. Naroditsky, K. Hanna, R.A.Y. Kolczynski, D.J. Loiacono, S. Mangru, M. Tinker, W.Y. Zhao	2006	Proceedings of the IEEE 94 (11), pp. 1936–1946	97 (61)
14. Toward non-cooperative iris recognition: A classification approach using multiple signatures	H. Proença, L.A. Alexandre	2007	IEEE Transactions on Pattern Analysis and Machine Intelligence 29 (4), pp. 607–612	79 (42)
15. How iris recognition works	J. Daugman	2002	IEEE International Conference on Image Processing 1, pp. I/33–I/36	77 (69)
16. Toward accurate and fast iris segmentation for iris biometrics	Z. He, T. Tan, Z. Sun, X. Qiu	2009	IEEE Transactions on Pattern Analysis and Machine Intelligence 31 (9), pp. 1670–1684	73 (31)
17. An effective approach for Iris recognition using phase-based image matching	K. Miyazawa, K. Ito, T. Aoki, K. Kobayashi, H. Nakajima	2008	IEEE Transactions on Pattern Analysis and Machine Intelligence 30 (10) , pp. 1741–1756	72 (34)
18. Iris segmentation methodology for non-cooperative recognition	H. Proença, L.A. Alexandre	2006	IEEE Proceedings: Vision, Image and Signal Processing 153 (2) , pp. 199–205	70 (36)
19. Experiments with an improved iris segmentation algorithm	X. Liu, K.W. Bowyer, P.J. Flynn	2005	4th IEEE Workshop on Automatic Identification Advanced Technologies pp. 118–123	65 (50)
20. FRVT 2006 and ICE 2006 large-scale experimental results	P.J. Phillips, W.T. Scruggs, A.J. O'Toole, P.J. Flynn, K.W. Bowyer, C.L. Schott, M. Sharpe	2010	IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (5), pp. 831–846	61 (8)

Table 9 The top 20 most significant conventions

Acronym	Convention name	TP	TP%
1. ICB	IAPR International Conference on Biometrics	40	4.06
2. ICIP	IEEE International Conference on Image Processing	35	3.55
3. ICPR	International Conference on Pattern Recognition	27	2.74
4. BTHI	Biometric Technology for Human Identification	25	2.54
5. BTAS	International Conference on Biometrics: Theory, Applications and Systems	20	2.03
6. ICCST	IEEE International Carnahan Conference on Security Technology	11	1.12
7. CISP	International Congress on Image and Signal Processing	11	1.12
8. CIB	IEEE Workshop on Computational Intelligence in Biometrics: Theory, Algorithms, and Applications	9	0.91
9. MMIPSA	Mobile Multimedia/Image Processing, Security, and Applications	9	0.91
10. ICWET	International Conference and Workshop on Emerging Trends in Technology	8	0.81
11. MIXDES	International Conference—Mixed Design of Integrated Circuits and Systems	7	0.71
12. ICIAR	International Conference on Image Analysis and Recognition	7	0.71
13. CIARP	Iberoamerican Congress on Pattern Recognition	6	0.61
14. ICACIA	International Conference on Apperceiving Computing and Intelligence Analysis	6	0.61
15. ICCIT	International Conference on Computer and Information Technology	6	0.61
16. CCBR	Chinese Conference on Biometric Recognition	5	0.51
17. AUTOID	IEEE Workshop on Automatic Identification Advanced Technologies	5	0.51
18. AVBPA	International Conference on Audio- and Video-Based Biometric Person Authentication	5	0.51
19. CVPRW	IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops	5	0.51
20. AIPR	IEEE Applied Imagery Pattern Recognition Workshop	4	0.41

comparison with the total amount of papers (1354) and category. Among the top 3 research topics, we find “Feature extraction” with 406 papers, followed by “Iris segmentation” with 246 papers and “Pattern matching” with 133 papers. According to the results of our ranking, 13 research topics were classified as ongoing, 5 as emerging and 2 as of decreasing over time. We notice a more substantial volume of research studies among the topics classified as ongoing: “Feature extraction”, “Iris segmentation” and “Pattern matching”. By contrast, the research topics “Non-ideal”, “Quality measures”, “Near Infra-red”, “Real time systems”, “Iris acquisition”, “Pupil localization”, “Eyelash detection”, “Spoof detection”, “Video sequences” and “Multiscales” also classified as ongoing, did not receive as much attention.

In spite of the fact that iris recognition is not a recent research field, the most relevant research proposals have emerged in the last 5 years. This represents more than half the production for the entire period under study. We observe a renewed interest for research in the areas of: “Visible light”, “Low resolution”, “Compression algorithms”, “Non-circular boundaries” and “Iris indexing” which had a notable production in the last years and were classified as emerging. By contrast, the research topics “Eyelid detection” and “Iris normalization” are going through a phase of decreasing number of publications as reflected in Table 11. Therefore, these topics do not seem promising avenues of research and can be considered as obsolete for the time being.

Table 10 The top 20 leading journals

Print-ISSN	Journal name	SJR	JCR	TP	TP%
1. 0162-8828	IEEE Transactions on Pattern Analysis and Machine Intelligence	8.094	4.795	15	4.08
2. 1057-7149	IEEE Transactions on Image Processing	2.835	3.199	3	0.82
3. 1083-4419	IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics	2.755	3.236	8	2.17
4. 0031-3203	Pattern Recognition	2.365	2.632	10	2.72
5. 0262-8856	Image and Vision Computing	1.839	1.959	8	2.17
6. 1051-8215	IEEE Transactions on Circuits and Systems for Video Technology	1.835	1.819	3	0.82
7. 1556-6013	IEEE Transactions on Information Forensics and Security	1.683	1.895	18	4.89
8. 1077-3142	Computer Vision and Image Understanding	1.653	1.232	7	1.90
9. 0165-1684	Signal Processing	1.453	1.851	4	1.09
10. 0957-4174	Expert Systems with Applications	1.358	1.854	5	1.36
11. 0167-8655	Pattern Recognition Letters	1.149	1.266	16	4.35
12. 0003-6935	Applied Optics	0.966	1.689	7	1.90
13. 0018-9456	IEEE Transactions on Instrumentation and Measurement	0.808	1.357	4	1.09
14. 0143-8166	Optics and Lasers in Engineering	0.796	1.916	7	1.90
15. 1380-7501	Multimedia Tools and Applications	0.646	1.014	3	0.82
16. 0218-0014	International Journal of Pattern Recognition and Artificial Intelligence	0.604	0.562	8	2.17
17. 0091-3286	Optical Engineering	0.437	0.880	11	2.99
18. 1812-5638	Information Technology Journal	0.402	-	4	1.09
19. 1687-6172	Eurasip Journal on Advances in Signal Processing	0.367	-	9	2.45
20. 1549-3636	Journal of Computer Science	0.296	-	6	1.63

Figure 6 shows the temporal evolution of three selected research topics classified under different categories. Figure 6a presents the temporal evolution of the "Feature extraction" topic classified as ongoing. The temporal evolution of the "Visible light" topic classified as emerging is shown in Fig. 6b. Figure 6c outlines the temporal evolution of the "Eyelid detection" topic classified as decreasing. In all these figures, the criterion presented in "Methodological approach" section to classify the outstanding research topics are drawn upon.

We concluded the analysis of the outstanding research topics by matching them with the most cited authors using the SOMs technique. In order to limit the scope of our paper, we have selected 6 out of the 20 research topics for our analysis. For this purpose, we selected 4 research topics closely related to the iris recognition stages and 2 other ones among the most productive of the emerging topics. Figure 7 shows the distribution of publications of the top 20 most cited authors for each selected research topic. This figure presents each research topic in descending order, taking into account the number of publications by each of the most cited authors.

According to Fig. 7, T. Tan and Z. Sun are the most productive authors for almost all research topics. However this is not true in the case of the topic emerging: "Visible light" for which the most prolific authors are H. Proença, followed by A. Ross. Let us mention that the top 20 most cited authors have been prolific in 3 research topics. In order of

Table 11 The top 20 outstanding research topics

Research topic	Paper production by year													TP	TP%	Category
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012			
1. Feature extraction	1	6	5	5	19	24	38	34	46	55	72	48	53	406	29.99	Ongoing
2. Iris segmentation	0	0	1	0	3	8	15	19	26	49	48	39	38	246	18.17	Ongoing
3. Pattern matching	1	2	2	1	4	7	17	12	16	21	22	15	13	133	9.82	Ongoing
4. Non-ideal	0	0	1	0	0	0	1	3	5	12	12	12	4	50	3.69	Ongoing
5. Quality measures	0	0	0	0	0	0	3	5	5	13	9	7	5	47	3.47	Ongoing
6. Near Infra-red	0	0	0	0	0	1	1	1	4	4	7	6	15	39	2.88	Ongoing
7. Real time systems	1	1	0	0	2	3	2	4	1	5	8	4	2	33	2.44	Ongoing
8. Visible light	0	0	0	0	0	0	0	0	4	4	7	4	13	32	2.36	Emerging
9. Iris acquisition	0	0	0	0	1	4	0	1	7	4	4	1	5	27	1.99	Ongoing
10. Pupil localization	0	0	0	0	0	1	1	0	3	2	8	3	7	25	1.85	Ongoing
11. Eyelash detection	0	0	0	1	1	0	3	1	4	1	2	3	0	16	1.18	Ongoing
12. Eyelid detection	0	0	0	0	2	0	2	0	6	3	1	2	0	16	1.18	Decreasing
13. Spoof detection	0	0	0	1	1	0	1	3	1	2	3	2	1	15	1.11	Ongoing
14. Low resolution	0	0	0	0	0	0	0	0	2	1	4	2	4	13	0.96	Emerging
15. Video sequences	0	0	0	0	0	0	1	0	0	3	2	4	1	11	0.81	Ongoing
16. Multiscales	0	0	0	0	0	0	1	1	1	1	4	1	1	10	0.74	Ongoing
17. Compression algorithms	0	0	0	0	0	0	0	1	0	2	1	3	2	9	0.66	Emerging
18. Iris normalization	0	0	0	0	1	2	1	1	1	1	1	0	0	8	0.59	Decreasing
19. Non-circular boundaries	0	0	0	0	0	0	0	0	1	1	3	2	1	8	0.59	Emerging
20. Iris indexing	0	0	0	0	0	0	0	0	2	0	0	2	2	6	0.44	Emerging

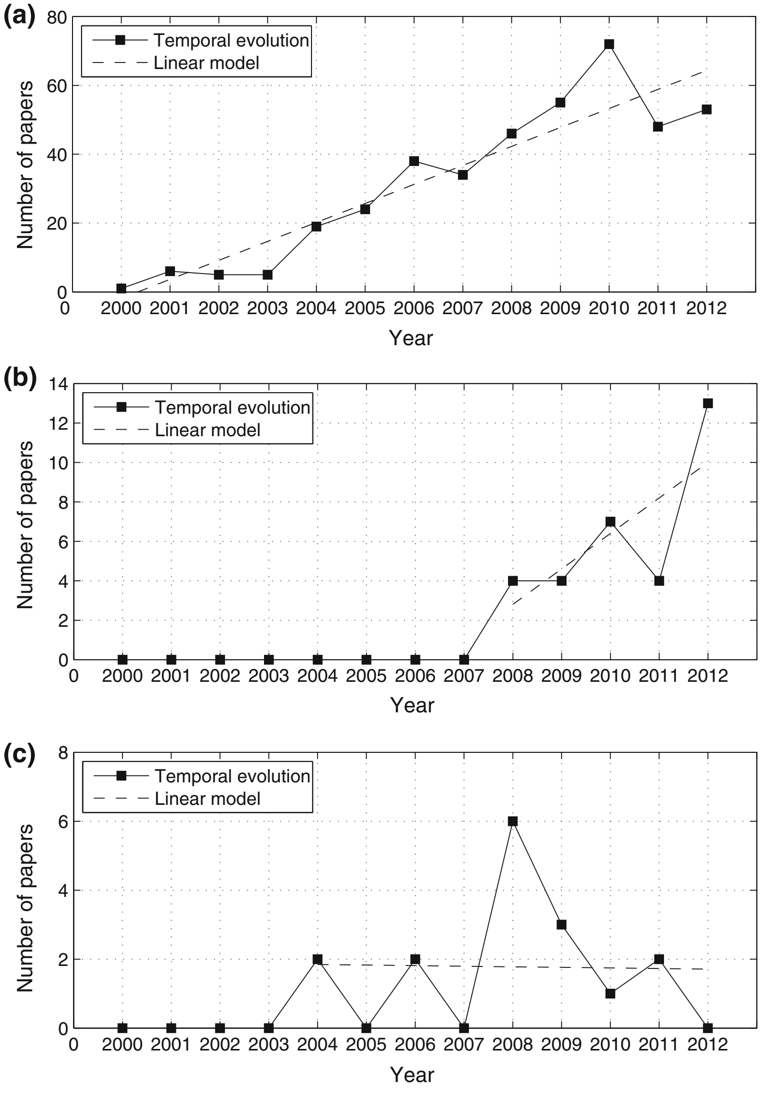


Fig. 6 **a** "Feature extraction" topic classified as ongoing. **b** "Visible light" topic classified as emerging. **c** "Eyelid detection" topic classified as decreasing

importance, these are "Pattern matching", "Iris segmentation" and "Feature extraction". Very few of the most cited authors have worked on the research topics:"Iris acquisition", "Visible light" and "Low resolution". In spite of the high impact of J. Daugman as we saw in the previous sections, the name of this author not appears among the researchers who have dealt with these three research topics.

Future researchers on iris recognition should be knowledgeable with the papers of the leading authors with more impact in the field since they are the ones whose contribution has been the most significant. They show the way by pointing out future directions and emerging topics. Among the authors who have worked substantially on the topics of

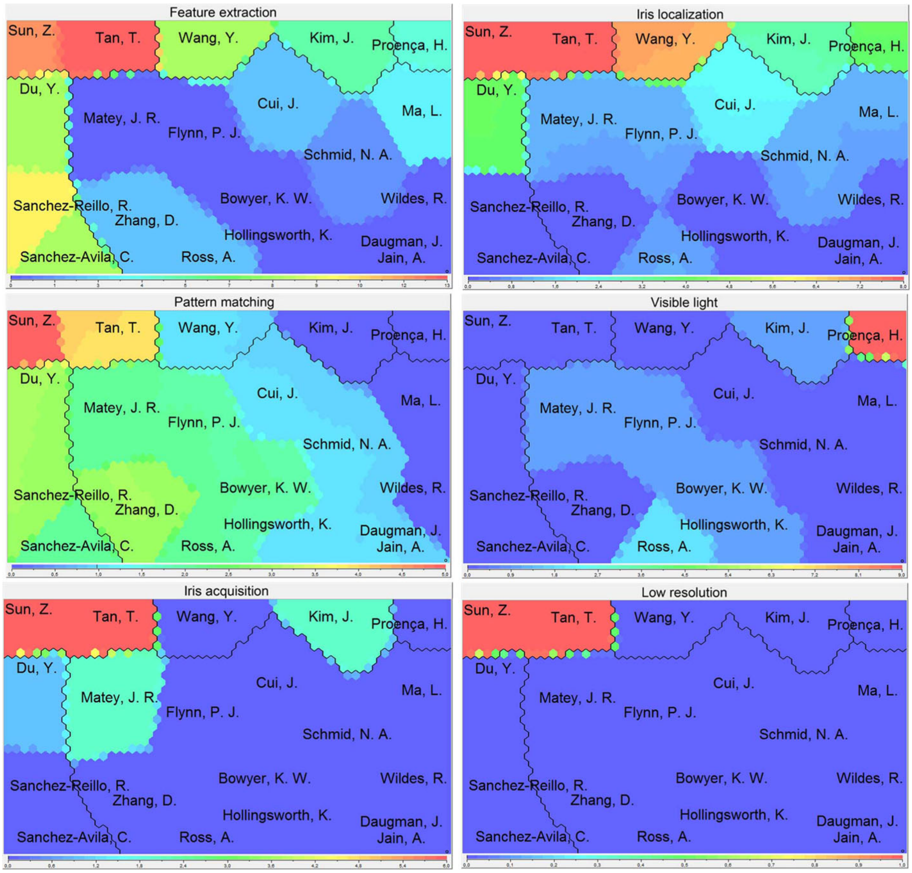


Fig. 7 Most cited authors in some outstanding research topics

emerging interest, let us mention J. Daugman, T. Tan, Z. Sun, H. Proença and A. Ross. Also it is important to specify that the research topics classified as ongoing and emerging concern the challenging field of non-ideal iris recognition. Non-ideal iris recognition refers to the recognition process in environments with less-constraints (e.g. without fixed distance, person movements, lighting conditions). These environments constitute additional difficulties to the complexity already mentioned for each stage of the iris recognition process. Therefore, the iris recognition field is still an open area for future research in order to meet the challenges caused by non-ideal conditions.

Conclusions

In this paper, we presented a comprehensive overview of the field of iris recognition using a bibliometric approach. Historical records, basic concepts, current progress and trends on iris recognition are presented as a way to introduce this field of research. This study underlines the advantages of using a bibliometric approach to obtain background information on a specific field of research, in our case iris recognition. It is particularly useful to new researchers as a guiding tool to identify some key elements of the research field. Thanks to the bibliometric analysis, we have been able to identify the temporal evolution, leading authors, most cited papers, significant conventions, leading journals and outstanding research topics and companies and patents. This analysis has been carried out on a pool of 1,354 papers in English indexed by the database Scopus in the period 2000–2012. As a result, we notice major advances in the publications on iris recognition. The main contributions in this field have taken place over the last 5 years, with 66 % of the total amount of publications in the period under study. According to our results, the ranking of the most productive authors does not match the ranking of the most cited authors. Therefore, we provided a more conclusive rank of the leading authors with the highest impact in the field based on measures of quality of scientific output and leadership. This should be kept in mind in future reviews of iris recognition studies. Besides, we presented the collaboration network among the top 20 most productive authors and the corresponding centrality measures such as: betweenness, closeness and degree. We found that most of the researchers work in teams and are inclined to collaborate with other research networks. The fact that J. Daugman has worked mainly as a single author might reflect in some way his level of leadership among the identified leading authors. As regards the significant conventions and leading journals, none deals exclusively with iris recognition. For example we can mention, the most productive convention is the “International Conference on Biometrics” with 40 papers and the most productive journal is the “IEEE Transactions on Information Forensics and Security” with 18 papers.

Furthermore, we were able to identify outstanding research topics which were classified into three main categories based on their corresponding number of publications over the period under study. This provides leads as to which research topics are worthy of further investigation and which areas of a specific topic should be focused on in order to make a significant contribution to the field. Thus, the research topics classified as ongoing and emerging suggest that the field of iris recognition is still an open area for further research avenues especially in the case of non-ideal iris recognition. In addition, we presented an analysis using the SOMs technique in order to identify the distribution of paper production of the top 20 most cited authors for 6 selected outstanding research topics. This bibliometric study is of limited help to assess the qualities or limitations of the procedure used in previous research works, as concerns the originality and reliability of the experimental methodology. Nevertheless, it constitutes an indispensable research tool to get a global overview of the current progress and trends in the field of iris recognition. In spite of its limitations due to the scope of the retrieved bibliographic material, this article provides a good starting point to understand the evolution of research in the field of iris recognition.

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