Nonlinear correlation by using invariant identity vectors signatures to identify plankton

Correlación no lineal utilizando firmas de vectores identidad para la identificación de plancton

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ABSTRACT

In this paper a new methodology to recognize radiolarians is presented. This system is invariant to position, rotation and scale by using identity vectors signatures (I_s) obtained for both the target and the problem image. In this application, I_s is obtained by means of a simplification of the main features of the original image in addition of the properties of the Fourier transform. Identity vectors signatures are compared using nonlinear correlation. This new methodology recognizes objects in a more simple way. It has a low computational cost of approximately 0.02 s per image. In addition, the statistics of Euclidean distances is used as an alternative methodology for comparison of the identity vectors signatures. Also, experiments were carried out in order to find the noise tolerance. The discrimination coefficient was used as a metric in performance evaluation in presence of noise. The invariant to position, rotation and scale of this digital system was tested with 20 different species of radiolarians and with 26 different species of phytoplankton (real images). The results obtained have a confidence level above 95.4%.

Keywords: image processing, invariant digital system, pattern recognition, plankton identification.

RESUMEN

En este trabajo se presenta una nueva metodología para el reconocimiento de radiolarios. Este sistema es invariante a posición, rotación y escala y utiliza firmas vectores identidad (I_s) tanto como para la imagen problema como para la imagen objetivo. En esta aplicación, I_s se obtiene mediante una simplificación de los rasgos totales de la imagen original tomando en cuenta las propiedades de la transformada de Fourier. Los vectores identidad son comparados entre sí mediante una correlación no lineal. Esta nueva metodología reconoce objetos de manera muy sencilla. Tiene un costo bajo computacional de aproximadamente 0.02 s por imagen. Además, de una manera alternativa se utiliza la estadística de distancia Euclidiana para comparar los vectores identidad. Se llevaron a cabo experimentos numéricos para encontrar la tolerancia del método al ruido en la imagen. La métrica matemática coeficiente de discriminación fue utilizada para evaluar el desarrollo del algoritmo en presencia de ruido. El sistema digital invariante a posición, rotación y escala fue evaluado con 20 diferentes especies de radiolarios y con 26 diferentes especies de fitoplancton (imágenes reales). Los resultados obtenidos tuvieron un nivel de confianza del 95.4%.

Palabras clave: procesado de imágenes, sistema digital invariante, reconocimiento de patrones, identificación de plancton.

INTRODUCTION

Radiolarians are holoplanktonic protozoa widely distributed in the oceans. They are present throughout the water column from near surface to hundreds of meters depth. As with many planktonic organisms, their abundance in a geographical region is related to quality of the water mass, including such variables as temperature, salinity, productivity, and available nutrients.

Radiolarians are characterized by the presence of a shell or skeleton radial configuration siliceous is the main attribute to identify species, especially sedimentary or fossilized (Campbell 1954; Kudo 1969). They significantly influence the oceanic silica cycle and their skeletons contributed to oceanic sediments and siliceous sedimentary rocks since, at least, the Ordovician (Grunau 1965; Daneliant 1999).

Currently, the radiolarians both fossil and recent, have achieved a great importance as hydrological indicators, paleoecological, palaeoclimatic and stratigraphic (Nigrini 1968; Lisitzin 1975; Casey 1977; Molina-Cruz 1977; Kling 1978; Boltovskoy 1981, 1987, 1989, 1991, 1994; Boltovskoy & Riedel 1987; Boltovskoy *et al.* 1993). The last decades have seen a significant increase in the practical value of radiolarians for biostratigraphy and palaeoceanography for all periods from the Cambrian onwards (Vishnevskaya & Kostyuchenko 2000; De Wever *et al.* 2001).

Similarities in skeletal structures between distantly related species and changes in these structures over the lifetime of a single individual, led to the conclusion that a new taxonomic system was needed (Hollande & Cachon-Enjumet 1960; Cachon & Cachon 1968, 1982, 1985; Petrushevskaya *et al.* 1976).In this way, the correct identification of an organism can take a long time and effort, the development of new techniques for species identification could be very useful for taxonomist.

These organisms include drifting animals, plants, archaea, algae, or bacteria that inhabit the pelagic zone of oceans, seas, or bodies of fresh water. Plankton is defined by their ecological niche rather than phylogenetic or taxonomic classification. Numerous studies have shown a strong relationship between larval fish survival and the timing and production of their food (*i.e.,* plankton) (Beaugrand 2005; Paerl *et al.* 2007; Gallego *et al*. 2012). The timing and production of plankton are in turn directly dependent on water temperature and nutrient availability (which is indirectly controlled by temperature-driven circulation patterns). Changes in climate can affect the timing of the seasonal plankton blooms, with effects that pass up the food web. Longer term changes in climate may even change the plankton species composition, changing the feeding environment of the larval fish.This is why the importance of opportune and efficient recognition of plankton in short time.

Pattern recognition is an expanding field in optical and computer research since the first appearance of the classical matched filter (Lugt 1964). Many advances have been made using different types of mathematical transformation taking advantage of their different properties such as invariance to position, rotation, and scale (Casasent *et al.* 1991; Vijaya-Kumar & Teck-Khim 1996; Zavala-Hamz & Álvarez-Borrego 1997; González-Fraga *et al.* 2006; Díaz-Ramírez *et al.* 2006; Guerrero-Moreno & Álvarez-Borrego 2009; Solorza & Álvarez-Borrego 2010).

In recent years, the methods of correlation are some of the most used techniques in a wide variety of areas (Álvarez-Borrego *et al.* 2002; Álvarez-Borrego & Castro-Longoria 2003; Mouriño-Pérez *et al.* 2006; Álvarez-Borrego & Fájer-Ávila 2006; Solorza & Álvarez-Borrego 2009, 2010; Lerma-Aragón & Álvarez-Borrego 2009; Hernández *et al.* 2010; Coronel-Beltrán & Álvarez-Borrego 2010). Also, these kinds of systems have been achieved that in addition to its high degree of reliability in objects recognition have low computational cost (Lerma-Aragón & Álvarez-Borrego 2009; Bueno-Ibarra *et al.* 2010).

The nonlinear correlation by using a k^{th} law is used to obtain the digital correlation providing information on the similarity between different objects. This kind of filter has advantages compared with the classical matched filter (Lugt 1964), the phase-only filter (Horner & Gianino 1984) and other linear filters; due to their great capacity to discriminate objects, the maximum value of the correlation peak is well localized, and the output plane is less noisy (Javidi 1990; Coronel-Beltrán & Álvarez-Borrego 2008). However, the novelty of this paper is the identity vector as well as its identity signature. This new methodology is used to recognize radiolarians, but it can be used for the recognition of other objects.

The procedure used in this work uses the original image statistical properties as well as the Fourier transform properties. This new methodology provides a significant reduction of the image information of size $m \times n$ to one-dimensional vector of 1×256 consequently with low computational cost. In addition, the statistics of Euclidean distances is used as an alternative methodology for comparison of identity vectors already transformed.

Related work

In the literature there are some works using different methods to identify or classify objects. For example, Dimitri *et al*. (2005) used global and local features classifiers applied to classify images of zooplankton acquired by the Video Plankton Recorder (Davis *et al.* 1992). The first component classifiers were a support vector machine (SVM) classifier trained on global features. The second classifier was non-parametric density (NPD) with local features. The accuracy was between 50 – 60 %. In addition, they used 8 NPD component classifiers increasing the accuracy to 62%. One of them was trained with local features, while the rest used global features.

Lowe (Lowe 1999) developed SIFT (Scale Invariant Feature Transform). This approach transforms an image into a large collection of local feature vectors, which are invariant to image translation, scaling, and rotation, and partially invariant to illumination changes and affine or

3D projection. The SIFT keys derived from an image are used in a nearest-neighbor approach to indexing to identify candidate object models which are used as input to a nearest-neighbor indexing method that identifies candidate object matches. Final verification of each match is achieved by finding a low-residual least-squares solution for the unknown model parameters. There are some modifications to this algorithm like PCA-SIFT (Principal Components Analysis-Scale Invariant Feature Transform) and GLOH (Gradient Location and Orientation Histogram) (Ke & Sukthankar 2004). Bay *et al* (2008) developed SURF (Speeded Up Robust Features) based in SIFT but with some improves.

Lerma-Aragón and Álvarez-Borrego (Lerma-Aragón & Álvarez-Borrego 2009) worked in the recognition of copepod species using a digital system with the utilization of vectorial signatures based on the well-known relation between scale and Fourier transform. They used the Euclidean distances as a method of comparison and they obtained a high confidence level (at least 95.4%).

Solorza and Álvarez-Borrego (Solorza & Álvarez-Borrego 2010) presented a correlation digital system invariant to position and rotation which uses uni-dimensional signatures (vectors) obtained using a binary ring mask constructed based on the real positive values of the Fourier transform of the corresponding image. They used linear and non-linear correlations and this methodology is applied in the classification of fossil diatoms images. Also, this system is tested using the diatoms images with additive Gaussian noise. The accuracy of this method was above 95.4%.

Fimbres-Castro *et al.* (2012) used vectorial signatures and spectral index to identify fossil diatoms. Vectorial signatures are calculated through several mathematical transformations such as Scale and Fourier transform with a procedure that achieves the most relevant information and reduce the bi-dimensional function to two vectors designed to be invariant to changes in position, rotation and scale. The second method used two values called spectral index which are calculated through several mathematical procedures which are used to recognize objects in a more simple way with a lower computational cost. The accuracy in these methods was at least 95.4%. In addition, they evaluated the method to distinguish the diatom in a noise background; two types of noise were added: salt & pepper and additive Gaussian. The system had the ability to recognize the diatom even with a density of around 0.65 of salt & pepper noise and a variance of around 1.26 of Gaussian noise with zero mean. There is so much to develop in this area. Not all the algorithms work well for any image. Some images can be defocused or with so much noise or with different illumination. However we must to consider three-dimensional information of the image and to reduce the identification analysis time. In the recent past, there were some groups which were considered to solve the identification analysis of plankton using mathematical algorithms; one of them was called SCOR WG 130 (http://www.scor-int.org/Working_Groups/wg130.htm). In the last years, Gorsky (Gorsky et al. 2010) developed the ZooScan, however with this system it is not possible to identify all the different species of plankton and thus there is so much research to do in this direction.

MATERIALS AND METHODS

Identity vectors are presented in order to significantly reduce the information and consequently the computational cost. Identity vectors are obtained through mathematical operations and transformations applied to the image. A nonlinear correlation between the target and the problem image is used. In general a nonlinear filter is defined by (Vijaya-Kumar & Hassebrook 1990)

$$NF = \left|F(u,v)\right|^{k} e^{-i\varphi(u,v)}, \quad 0<k<1, \tag{1}$$

Where $\left|F(u,v)\right|$ represents the modulus value of the Fourier transform of the image, k is the nonlinear strength factor that takes values between zero and one and $\varphi(u,v)$ is the phase of the Fourier transform. We can manipulate the discriminate capacities of the nonlinear processor changing the k values in this interval and therefore determine the best k of the nonlinear filter. In this digital system $k = 0.3$ isused.

Identity Vector Signature

The procedure to obtain the identity vector and its respective signature is shown in Figure 1. First, the image to be recognized is denoted by $f(x, y)$ where x and y are spatial coordinates in the Cartesian plane. In the step 1, a vector of 256 elements is created and denoted by $h(m)$,which represents the values in grayscale of the image with a range of values from 0 to 255 (histogram); where 0 represents the black color (assigned to $h(1)$) and 255 represents the white color (assigned to $h(256)$). In other words, in each m position of the vector $h(m)$, the pixel number which has the $m-1$ value (grayscale) in the function $f(x, y)$, will be assigned.

Thus, when the vector $h(m)$ is created, the rotation invariance is obtained. This happens because even if the object in the image is rotated the vector will be conserved. However, when the object in the image presents some scale changes, the vector $h(m)$ is affected, i.e.as the scale increases, the frequencies of the vector $h(m)$ also increase. In the same way, when the scale decreases the frequencies of the vector $h(m)$ decrease too. In order to solve this scale problem the identity vector, id_{vec}, is calculated by

$$id_{vec}(m) = \frac{h(m)}{pixel_{num}} \cdot m, \tag{2}$$

where $pixel_{num}$ is obtained by

$$pixel_{num} = \sum h(m) \cdot \tag{3}$$

In this way, regardless of whether the scale increase or decrease, the information obtained from the ratio $h(m)/pixel_{num}$ will be the same, maintaining constant theoretically this ratio. In addition, this ratio is multiplied by m value in order to create a significant difference between two similar id_{vec}. The result of the equation (2) is shown in step 2.

Therefore, each image has its respective id_{vec} which in theory must be conserved, even if the object is rotated or scaled. However, in some cases we find aliasing due to rotation or scale of the image. All the morphological aspects of the image were used when the id_{vec} is calculated.

Figure 2 shows an example of the vector $h(m)$ for the same image with different angles of rotation and different scale when the invariances are obtained. Theoretically the vector $h(m)$ must be the same, in the case of the rotation, variations may occur due to the saw tooth effect presented when the object is rotated. In the case of the scale, the vector $h(m)$ has different values due to the increase or decrease of the pixel number when the image is scaled. In order to solve this kind of problem, as the figure 4 shows, the ratio between the vector $h(m)$ and the $pixel_{num}$ is performed, small variations may occur due to aliasing. Finally the id_{vec} is obtained.

The modulus of Fourier transform is calculated in order to obtain the id_{vec} signature which is denoted by I_s and it is obtained as (step3)

$$I_s(w) = \left| \Im\{id_{vec}(m)\} \right|, \tag{4}$$

where $\Im$ represents the Fourier transform of the function id_{vec} and $|\,|$ represents the modulus.

Figure 3 shows the behavior of the signature I_s of the same image rotated from 1 deg to 180 deg in increments of 1 deg and scaled from 80% to 125% in increments of 1% which theoretically should not vary; however there are some variations which modify I_s, e.g. the saw tooth effect and aliasing. These effects can be seen especially in the high frequencies.

Figure 4 shows the difference between id_{vec} and I_s of the different objects, i.e. each image has its particular identity vector as well as its respective signature.

Nonlinear correlation between I_s^t and I_s^p

Figure 5 shows the procedure to identify the target. First of all, it is necessary to obtain the identity vector signature (Figure 1) of the target which is denoted by I_s^t and the identity vector signature of the problem image (image that could be or not the target) which goes through the same procedure (Figure 1) and it is denoted by I_s^p.

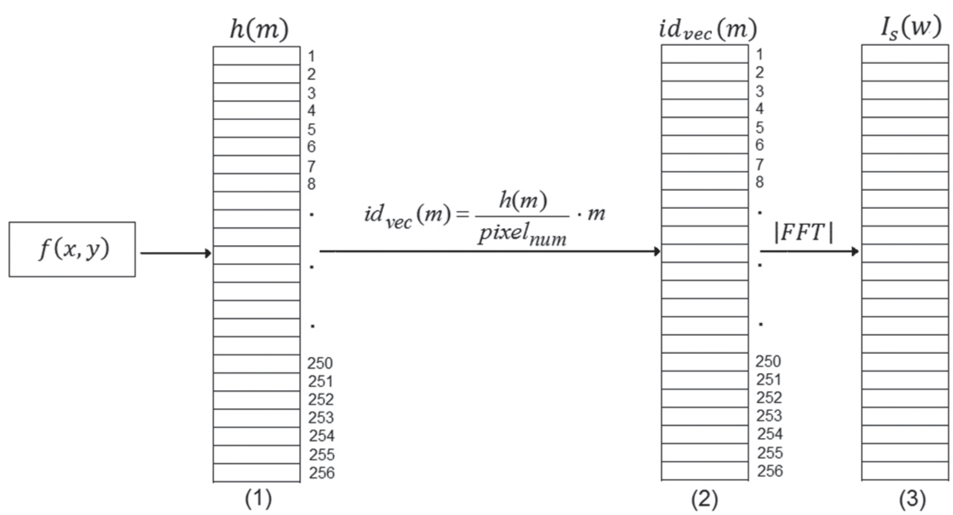

Figure 1.Procedure to obtain the identity vector signature.

Figura 1. Procedimiento para obtener la firma del vector identidad.

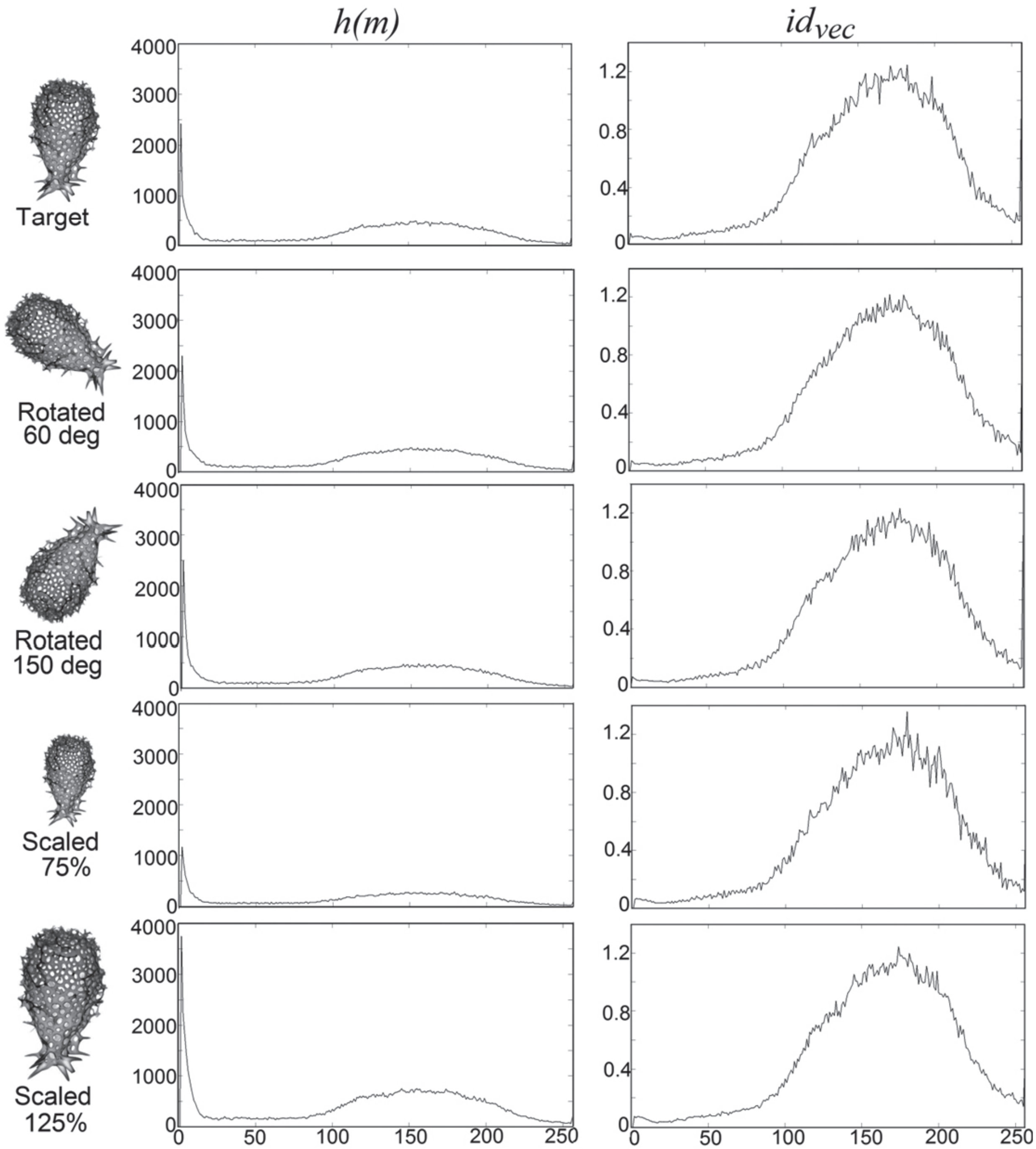

Figure 2. Example of each step to obtain the identity vector for the same organism with different variations.

Figura 2. Ejemplo de cada paso para obtener el vector identidad para el mismo organismo con diferentes variaciones.

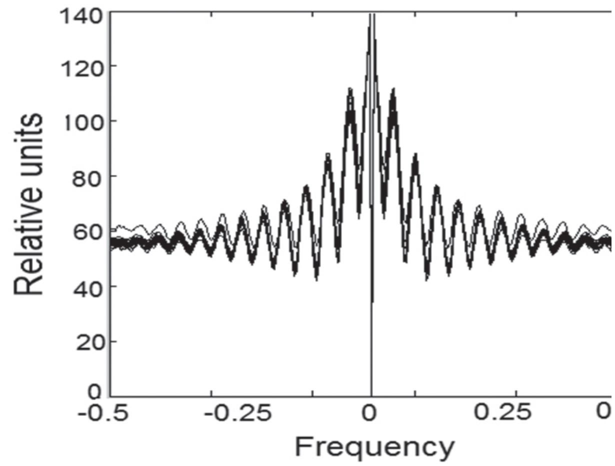

FIGURE 3.Example of the signature I_s when the same image is rotated from 1 deg to 180 deg and escalating from 80% to 125%.

FIGURA 3. Ejemplo de I_s cuando la misma imagen es rotada de 1 grado a 180 y escalada de 80% a 125%.

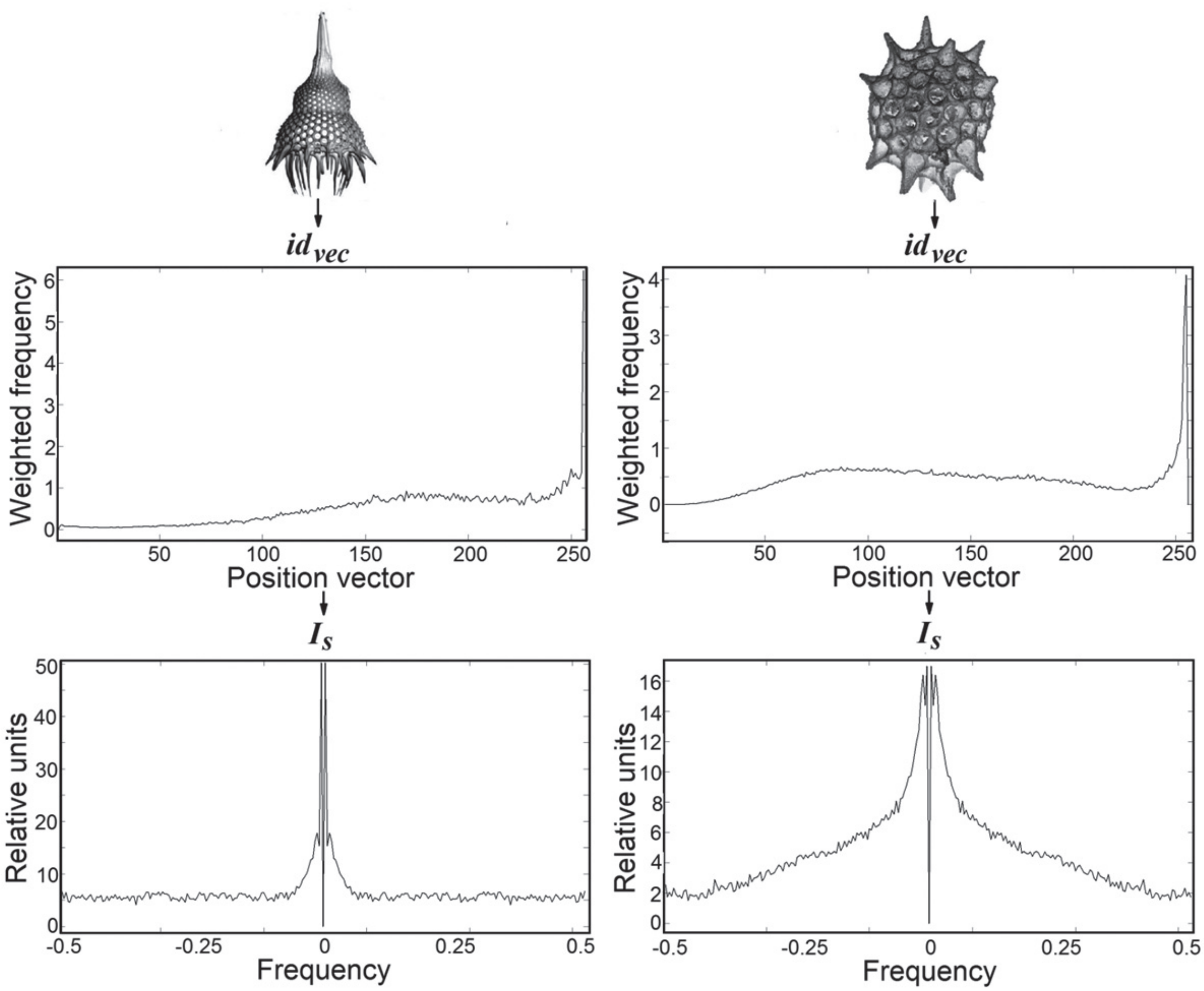

FIGURE 4. Example of the procedure to obtain the identity vector signature.

FIGURA 4. Ejemplo del procedimiento para obtener la firma del vector identidad.

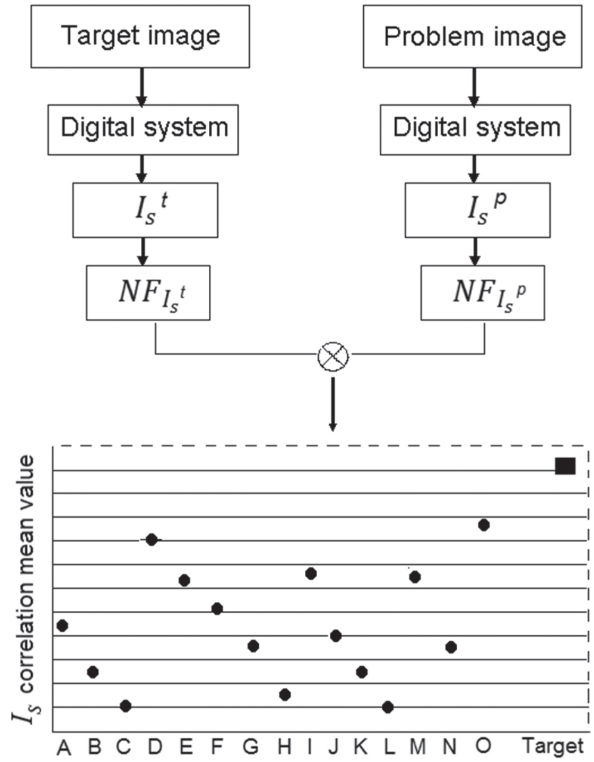

Figure 5.General procedure of identity vector signature nonlinear correlation.

Figura 5. Procedimiento general de la correlación no lineal de la firma del vector identidad.

Thus, when $I_s^{\,t}$ and $I_s^{\,p}$ are obtained, these signatures are compared using the nonlinear correlation (*k*-law). The symbol ⊗ means correlation between the target and the problem image. When an image is the same to the target, the correlation value is 1 or close. Otherwise, if the problem image is different to the target, the correlation value is so different to 1.

Identification of the target image by using Euclidean distance

When the target signature ($I_s^{\,t}$) and the problem image signature ($I_s^{\,p}$) have been obtained, the similarity between both signatures $I_s^{\,t}$ and $I_s^{\,p}$ is calculated using the statistics of Euclidian distances (d_E) like

$$d_E = \sqrt{\sum_{w=1}^{256} (I_s{}^t(w) - I_s{}^p(w))^2} \quad . \qquad (5)$$

Thus, the signature I_s of all p images of the image bank (4520 images) can be compared with any image t to be recognized.

Metric used in performance evaluation in presence of noise

The discrimination coefficient (also known as discrimination capability) was used in this work, which is formally defined (Vijaya-Kumar & Hassebrook 1990) as the ability of a filter to distinguish a target among other different objects. Considering that an object is embedded in a noise background, the discrimination coefficient would be given by

$$DC = 1 - \frac{\left|C^N(0,0)\right|^2}{\left|C^{OBJ}(0,0)\right|^2} \quad , \qquad (6)$$

where the correlation peak produced by the object to be recognized would be C^{OBJ} and the highest peak of just the noise background would be C^N. Thus, we refer to the confidence level of a given filter as the probability of confidence to recognize the target in the input scene. In the equation (6) we can deduce that the maximum value of DC tends to one ($C^{OBJ} >> C^N$), while negative values ($C^{OBJ} << C^N$) indicates that the object cannot be recognized.

RESULTS AND DISCUSSION

Radiolarians

To evaluate the performance of this digital system, 20 test images of different species of radiolarians were used (Figure 6). The images were taken from an internet site called radiolaria.org, which is an online database that contains information about extant and fossil radiolarians, with images, descriptions, references of researchers and taxonomists who are dedicated to the study of them. The selected images are JPEG format, which is a commonly used method of lossy compression for digital photography (image), which means that when the image is unzipped or displayed it loses relevant information of the image before compression. This format was chosen due to the importance of testing the system with images of low quality because if even with this kind of image the system works efficiently recognizing objects, obviously it will also do it with good quality images.

Each image used in the digital system was a 600 x 600 pixel image in gray scale. The images were rotated 180 deg in increments of 1deg and scaled from 80% to 125% in increments of 1%. An image bank of 4520 data was obtained (180 rotations + 46 scales= 226 variations for each one of the 20 radiolarians resulting 4520 images). Figure 7 shows some radiolarians and how they look with the respective changes in rotation and scale.

To perform the simulations, a computer Hewlett-Packard Model HP Pavilion dv7 Notebook PC with Intel® Core™ i7 CPU Q720 @1.60GHz processor, 6.0 GB of RAM was used. In this algorithm a k=0.3 was used.

phytoplankton images

In order to evaluate the performance of this digital system with good quality real images, 26 test images of different phytoplankton species were used (Figure 8). The images were taken in the mouth of the Gulf of California.

Each image used was 1800 x 1800 pixel image in gray scale. The images were rotated 180 deg in increments of 1deg and scaled from 80% to 125% in increments of 1%. An image bank of 5876 data was obtained (180 rotations + 46 scales = 226 variations for each one of the 26 plankton images resulting 5876 images).

In order to see if this technique works with a good performance, 20 different species of radiolarians (Figure 6) were used, with the characteristics mentioned above. However, this system could be used for any image recognition.

Figure 9 shows an example of this new methodology using the nonlinear correlation as a method of comparison between the signatures. The radiolarian *Zygocircus productos capulosus* (I) was selected as target; it was compared with each one of the 20 different species of radiolarians rotated and scaled images (4520 images).Figure 9 shows a clearly identification of the target without any kind of overlap and a very good separation between the target and the other images is shown. Statistic was performed and the mean value ±2SE (two standard error) was calculated. This algorithm has at least a 95.4% of confidence level for this case.

Also, *Plectopyramis dodecomma* (J) was taken as target and it was compared with the image bank (Figure 10). The target could be recognized with a confidence level above 95.4%. In the same way, 20 species of radiolarians were selected as target and were compared with the image bank in order to verify the results in each case. The results in all the cases were very similar to those shown in Figure 9 and 10, i.e. all the cases presented a confidence level of at least 95.4% (results are not shown). In terms of computational cost, this new methodology takes about 0.02 s per image.

Intended to confirm that this technique works efficiently, the statistics of Euclidean distances was used as an alternative comparison. Thus, the radiolarian *Zygocircus productos capulosus* (I) was selected as target and it was compared with each one of the image bank using the statistics of Euclidian distances (Figure 11). In the same way, *Plectopyramis dodecomma* (J) was selected as target and the result obtained is shown in Figure 12.

As the figures shown (Figures 11 and 12) the target could be recognized in both cases without any kind of overlap with a confidence level over 95.4%. Therefore, each one of the 20 images were taken as target and were compared using the statistics of Euclidean distances, the results obtained had at least 95.4% of confidence level for all the cases (results are not shown).

In order to evaluate the ability of our method to distinguish the radiolarians in a noise background, two types of noise were added: salt & pepper and additive Gaussian. Figures 13-14 show the discrimination coefficient (*DC*) means for I_s with an upper and lower limit indicating 95% of confidence level. 36 samples were used in each calculation. The noise added had a zero mean and variance or density as shown in the graph (x axis). In equation (6), the *DC* will be above zero only if the correlation peak of the object to be recognized is bigger than the correlation peak of noise.

The DC mean when Gaussian noise is added to the image is shown in Figure 13. The variability of variance is shown in x axis. Our system can recognize the object with a noise variance of around 0.85, i.e. the system has the ability to recognize the object until these limitations. Figure 14 shows the DC mean when noise salt and pepper is added to the image. The object can be identified with a density of around 0.98.

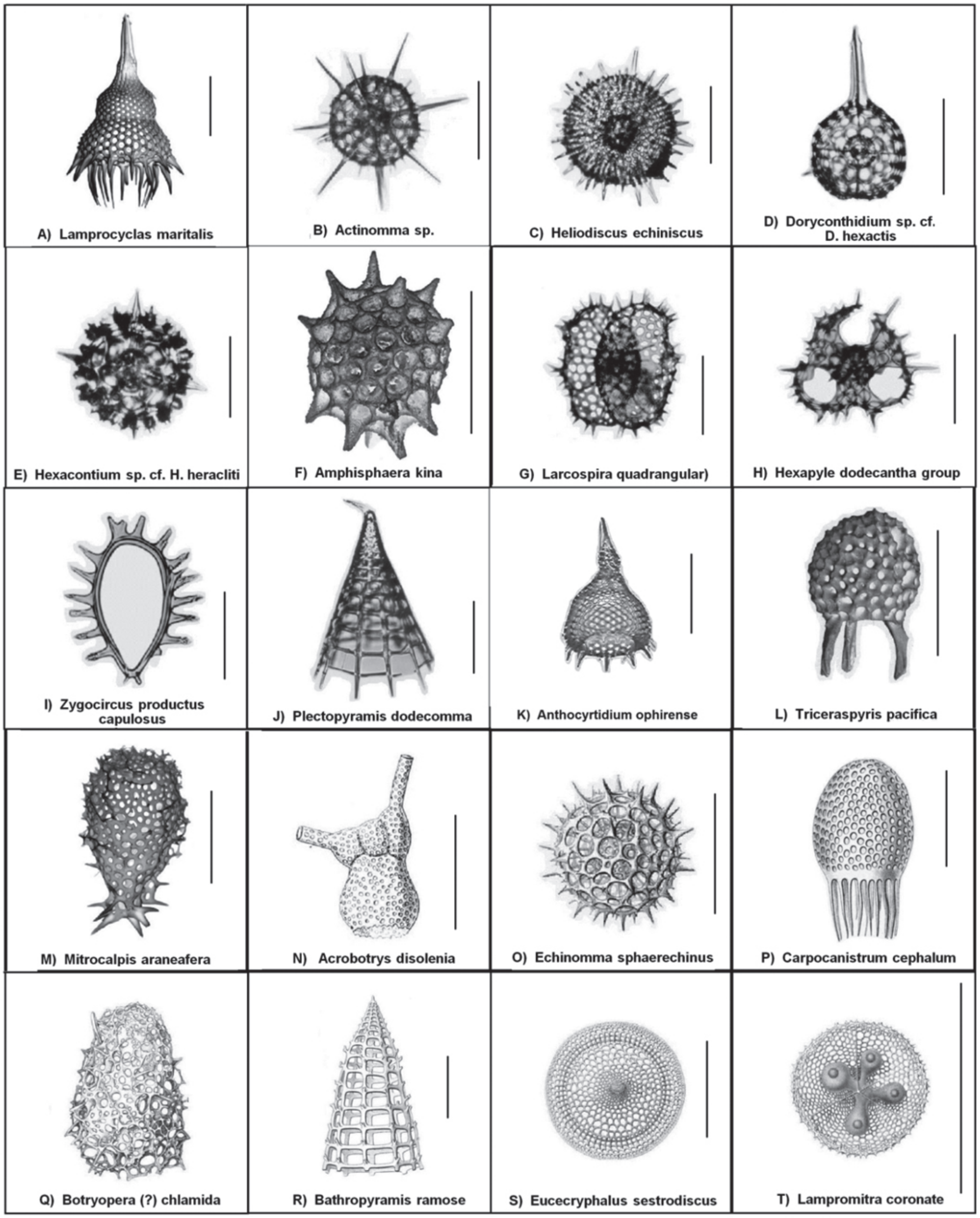

Figure 6. Radiolarians used in the digital system (bar = 100μ).

Figura 6. Radiolarios utilizado en el sistema digital (barra = 100μ).

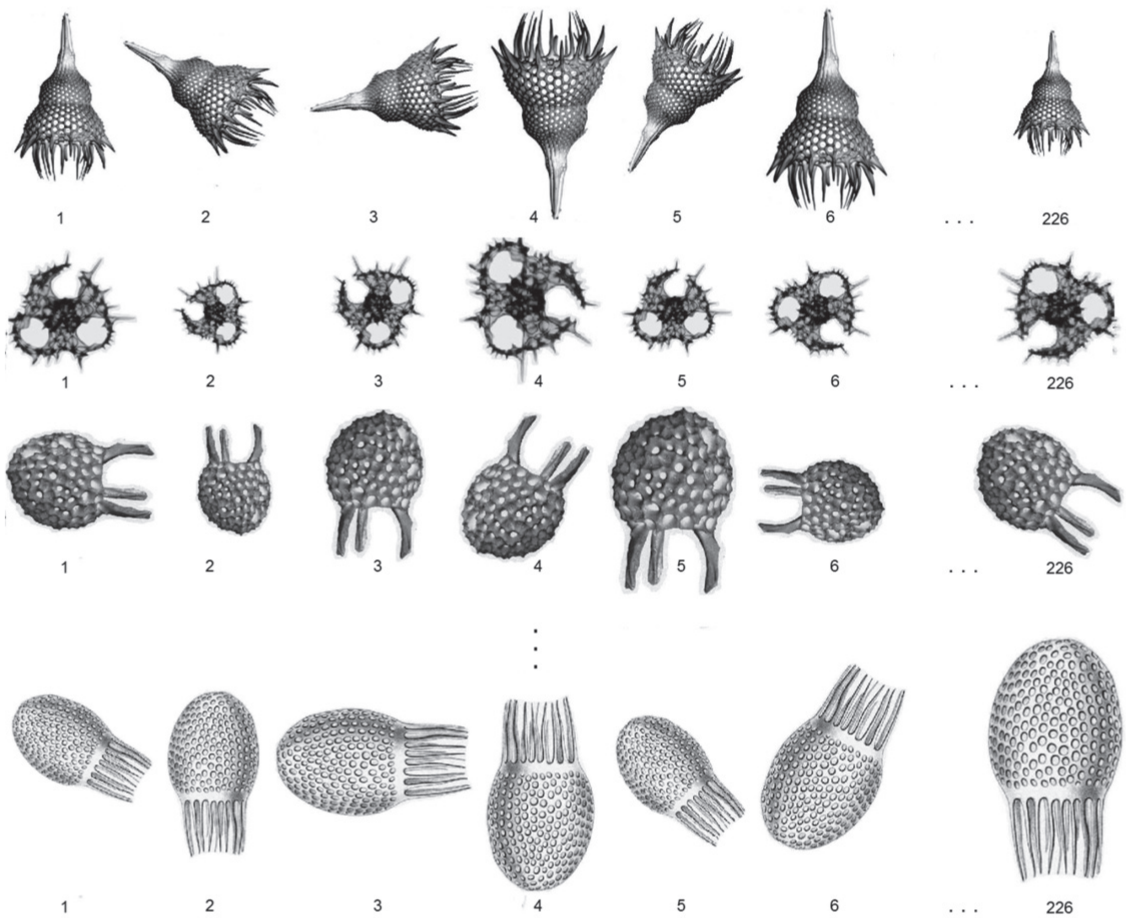

Figure 7. Species of radiolarians with changes in rotation and scale.

Figura 7. Especies de radiolarios con cambios en rotación y escala.

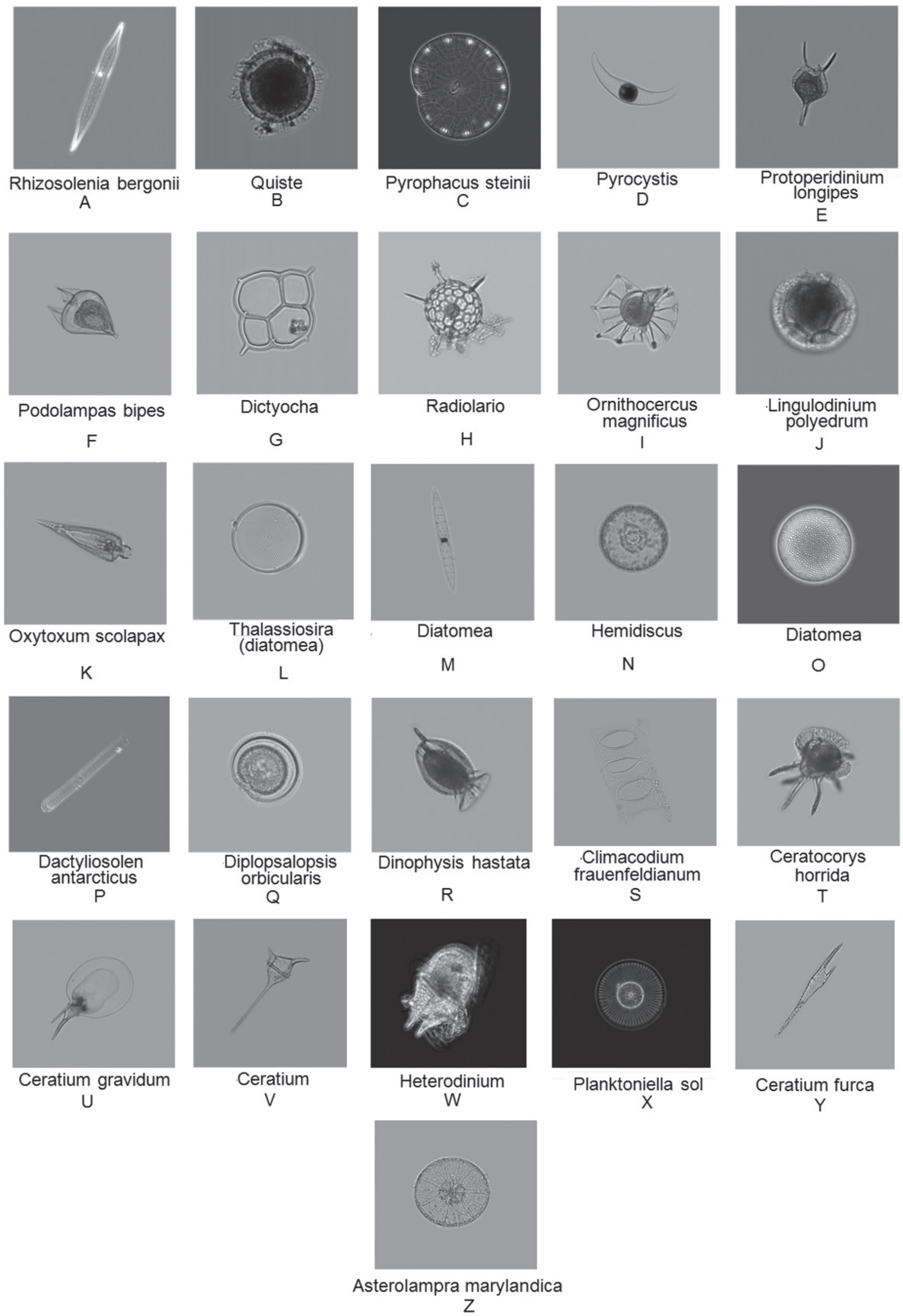

Figure8. 26 different species of plankton used in this digital system.

Figura8. 26 especies diferentes de plancton utilizadas en el sistema digital.

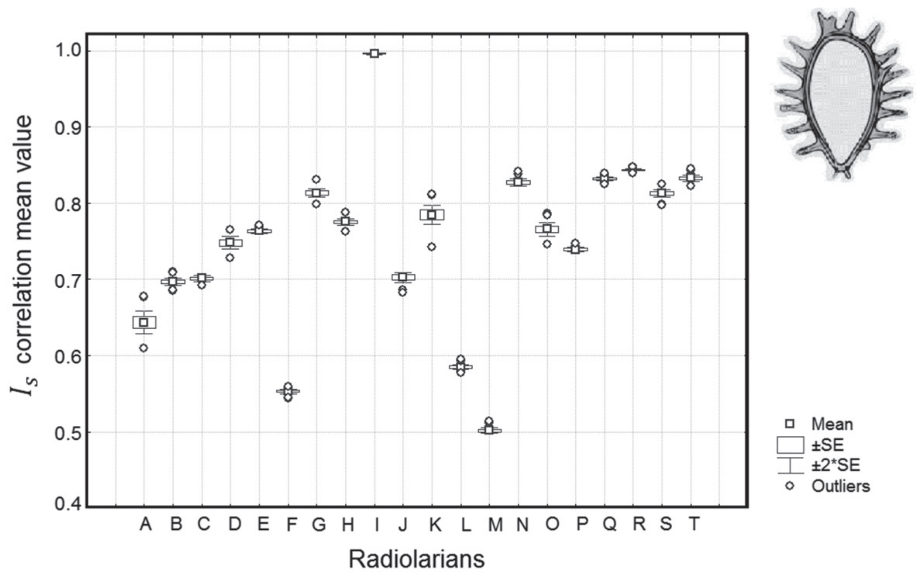

FIGURE 9. Nonlinear correlation plane of I_s where *Zygocircus productos capulosus* (I) is taken as target.

FIGURA 9. Plano de correlación no lineal de I_s donde *Zygocircus productos capulosus* (I) es tomada como imagen objetivo.

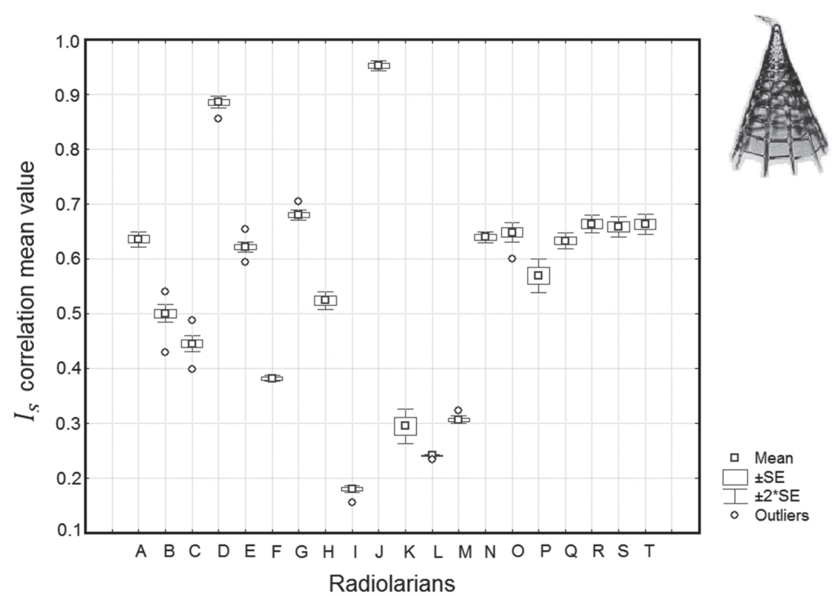

FIGURE 10. Nonlinear correlation plane of I_s where *Plectopyramis dodecomma* (J) is taken as target.

FIGURA 10. Plano de correlación no lineal de I_s donde *Plectopyramis dodecomma* (J) es tomada como imagen objetivo.

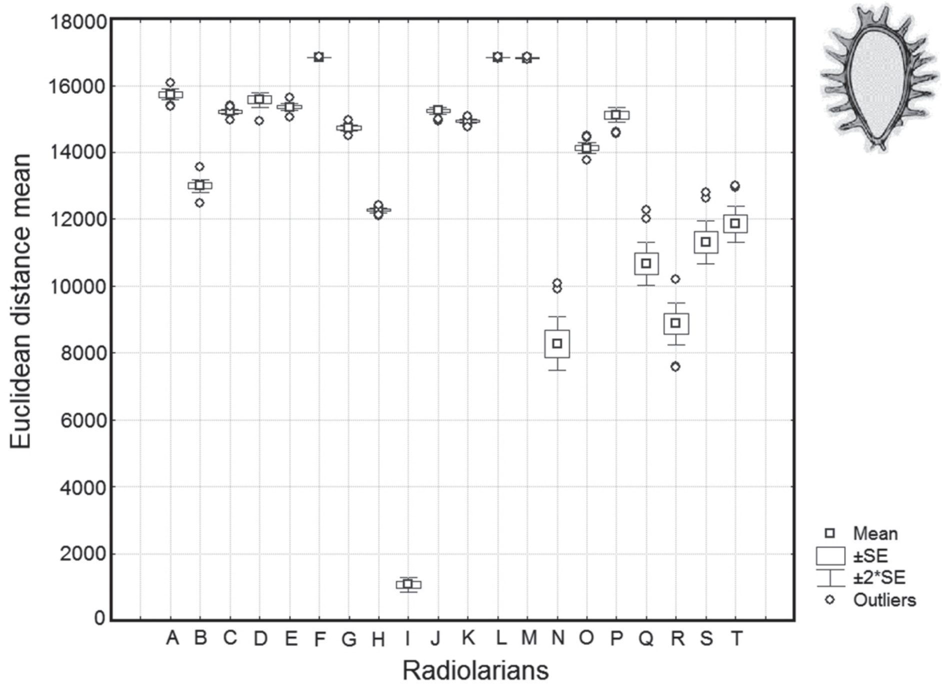

Figure 11. Statistical behavior of Euclidean distances using *Zygocircus productos capulosus*(I) as target.

Figura 11. Comportamiento estadístico de las distancias Euclidiana utilizando *Zygocircus productos capulosus* (I) como imagen objetivo.

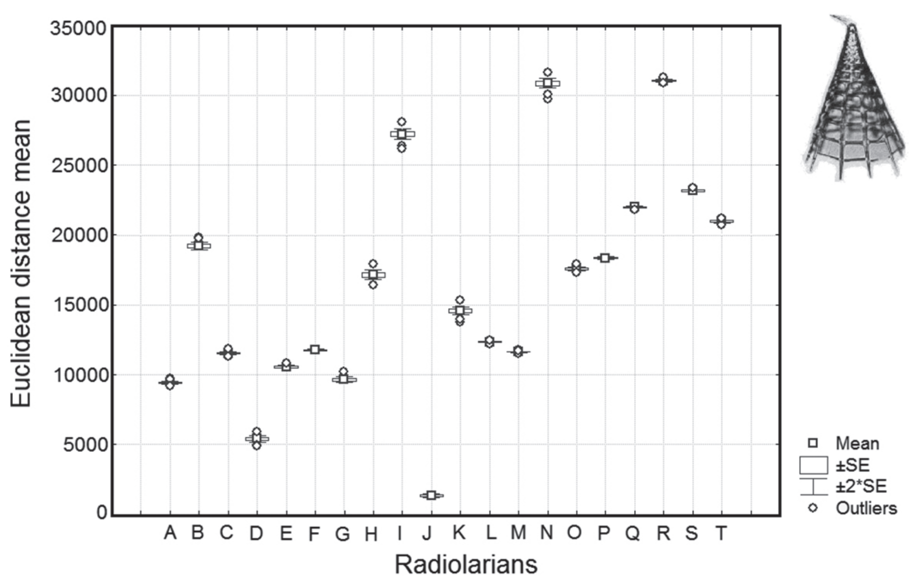

Figure 12. Statistical behavior of Euclidean distances using *Plectopyramis dodecomma*(J) as target.

Figura 12. Comportamiento estadístico de las distancias Euclidiana utilizando *Plectopyramis dodecomma* (J) como imagen objetivo.

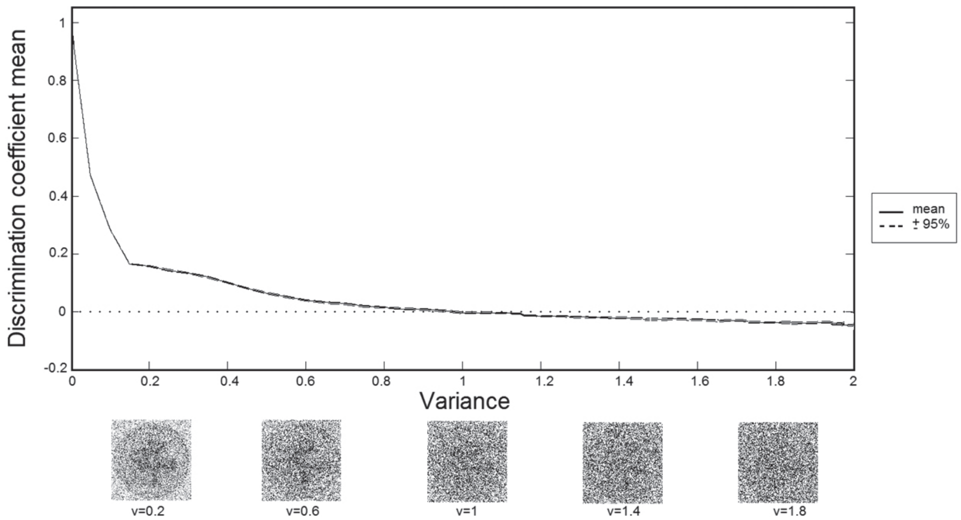

FIGURE 13.Performance of the system in presence of Gaussian noise.

FIGURA 13. Desempeño del sistema en presencia de ruido Gaussiano.

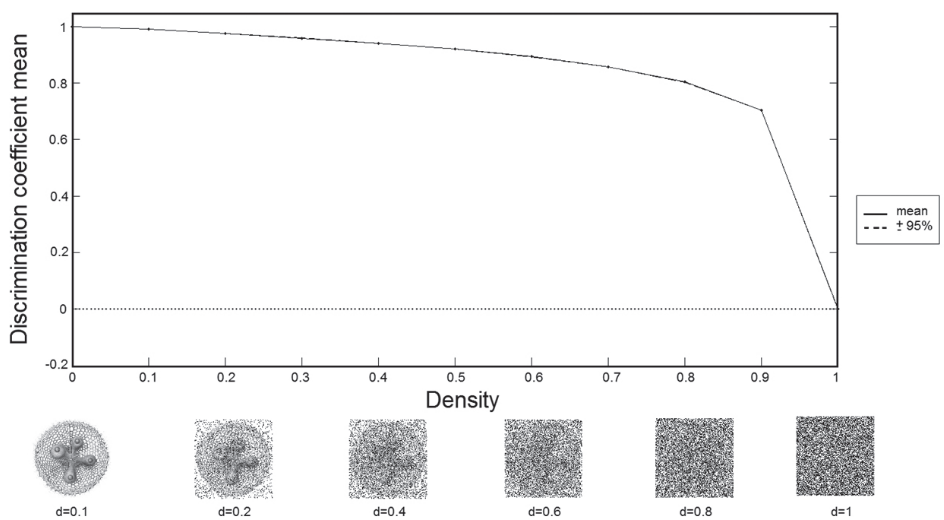

FIGURE 14. Performance of the system in presence of salt & pepper noise.

FIGURA 14. Desempeño del sistema en presencia de ruido sal y pimienta.

Figure 15 shows the *DC* mean when a combination of salt and pepper and Gaussian noises are added to the image, where the variations of the density is shown in *x* axis and the variations of the variance is shown *y* axis. The system has the ability to recognize the object according of the density of salt and pepper noise and the variance of Gaussian noise, i.e. depending of these values will be the maximum values of each type of noise that the system support to recognize the object. For example, when the variance of Gaussian noise is around of 0.7 the system supports a density of 0.1 of salt and pepper noise. In other hand, if the variance of Gaussian noise is around 0.3 the system supports a density of around 0.9 of salt and pepper noise.

In order to see if this technique works with a good performance with real images, 26 different species of plankton (Figure 8) were used, with the characteristics mentioned above.

Figure 16 shows an example of this new methodology using the nonlinear correlation as a method of comparison between the signatures. *Pyrophacus steinii* (C) was selected as target; it was compared with each one of the 26 different species of plankton rotated and scaled images (5876 images). Figure 16 shows a clearly identification of the target without any kind of overlap and a very good separation between the target and the other images is shown. Statistic was performed and the mean value ±2SE (two standard error) was calculated. This algorithm has at least a 95.4% of confidence level for this case.

Also, *Ornithocercus magnificus* (I) was taken as target and it was compared with the image bank (Figure 17). The target could be recognized with a confidence level above 95.4%. In the same way, Figure 18 shows the output correlation plane when *Protoperidinium longipes* (E) was selected as target and it was compared with the image bank, the target could be recognized with a confidence level above 95.4%.

Similarly, the 26 species of plankton were selected as target and were compared with the image bank in order to verify the results in each case. The results in all the cases were very similar to those shown in Figure 16, 17 and 18, i.e., all the cases presented a confidence level of at least 95.4% (results are not shown).

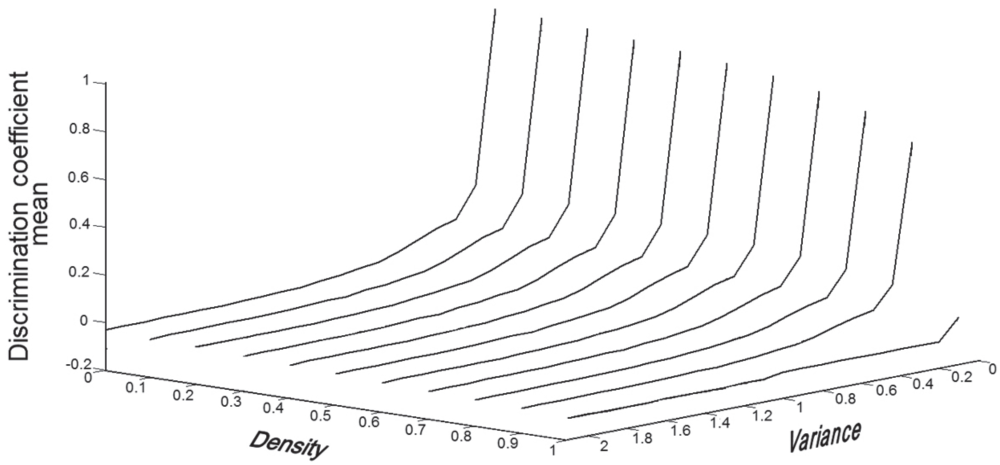

Figure 15.Performance of the system in presence of salt & peper noise adding Gaussian noise.

Figura 15. Desempeño del sistema en presencia de ruido sal y pimienta además de ruido Gaussiano.

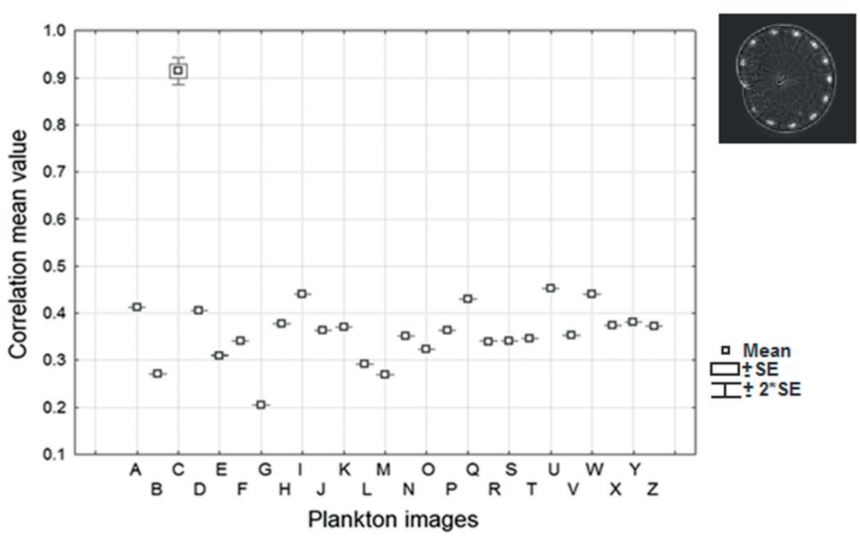

Figure16. Nonlinear correlation plane of I_s where *Pyrophacus steinii* (C) is taken as target.

Figura16. Plano de correlación no lineal de I_s donde *Pyrophacus steinii* (C) es tomada como imagen objetivo.

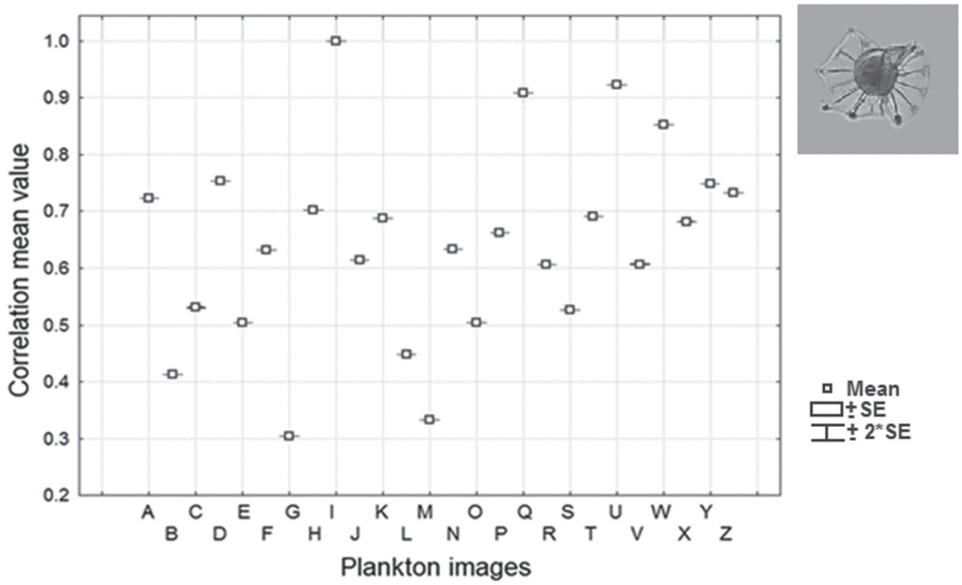

FIGURE 17. Nonlinear correlation plane of I_s where *Ornithocercus magnificus* (I) is taken as target.

FIGURA 17. Plano de correlación no lineal de I_s donde *Ornithocercus magnificus* (I) es tomada como imagen objetivo.

The statistics of Euclidean distances was used as an alternative comparison with the plankton real images (Figure 8). Thus, *Heterodinium* (W) was selected as target and it was compared with each one of the image bank using the statistics of Euclidian distances (Figure 19). In the same way, *Diplopsalopsis orbicularis* (Q) was selected as target and the result obtained is shown in Figure 20.

As the figures shown (Figures 19 and 20) the target could be recognized in both cases without any kind of overlap with a confidence level over 95.4%. Therefore, each one of the 26 images were taken as target and were compared using the statistics of Euclidean distances, the results obtained had at least 95.4% of confidence level for all the cases (results are not shown).

COMPARISON WITH OTHER ALGORITHMS

The algorithm was compared with respect to the one published by Fimbres-Castro, et al. (2011), the methodologies presented in that work had an accuracy above 95.4 % very similar than our methodology; in terms of computational cost comparing with them our methodology is about 0.02s per image in contrast with their system which is at least 3.8s.

In the other hand, our algorithm works very well with a very big addition of salt and pepper noise (about 98%) against their methodology which had a tolerance of 68%. However, in the case of Gaussian noise, our system had the ability to recognize the object with a variance of around 0.85 and their system a variance of 1.26. Thus, SIFT and SURF algorithms had a performance below these values.

To perform the simulations, a computer Hewlett-Packard Model HP Pavilion dv7 Notebook PC with Intel® Core™ i7 CPU Q720 @ 1.60GHz processor, 6.00 GB of RAM was used. Matlab platform was used. All the morphological aspects of the image were used when the id_{vec} is calculated.

The results show that identity vectors and their respective signatures are an efficiently methodology to identify objects and provide the necessary information to identify the object despite the significant reduction of information. This methodology has a confidence level of at least 95.4% and it has a low computational cost about 0.02 s per image. On the other hand, this new recognition methodology had a good performance using a nonlinear correlation as well as using the statistics of Euclidean distances with a confidence level of at least 95.4% in both comparison methods. Thus, this methodology has good performance using low quality images as well as good quality real images.

Gaussian and salt & pepper noise were added to the problem image. The system has the ability to recognize the radiolarian even with a variance of around 0.85 of Gaussian noise with zero mean and a density of around 0.95 of salt & pepper noise.

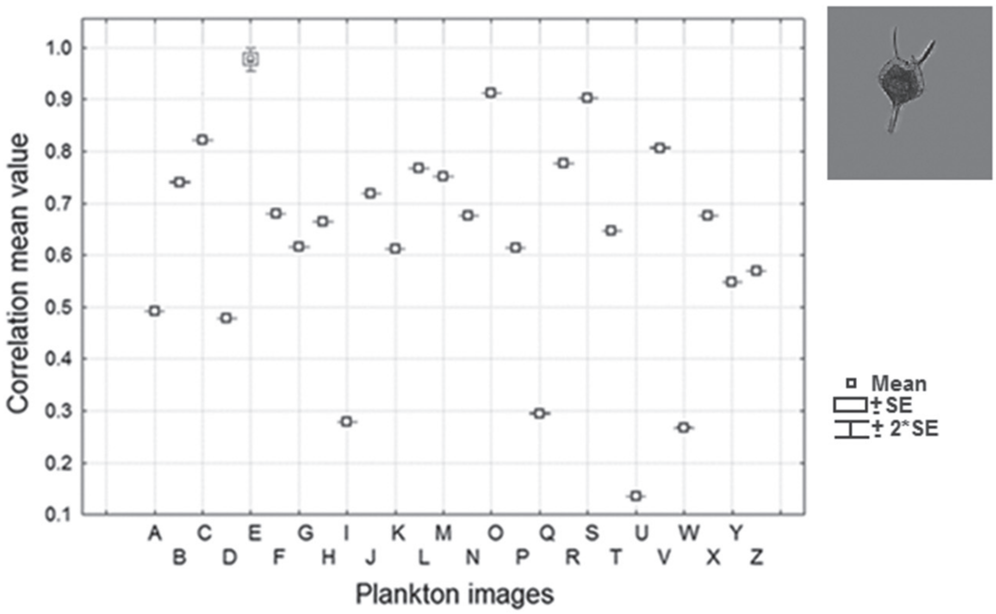

Figure 18. Nonlinear correlation plane of I_s where *Protoperidinium longipes* (E) is taken as target.

Figura18.Plano de correlación no lineal de I_s donde *Protoperidinium longipes*(E) es tomada como imagen objetivo.

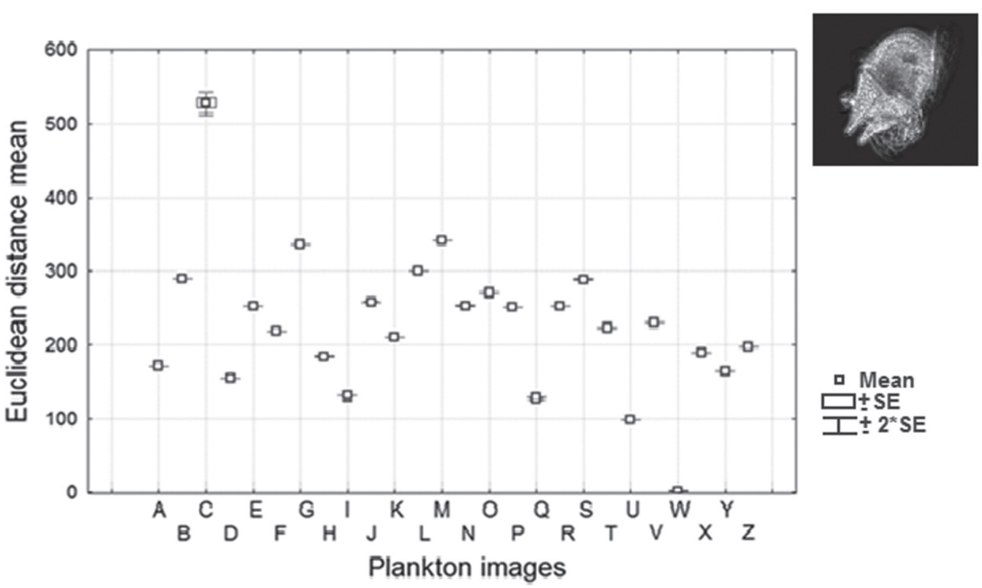

Figure 19. Statistical behavior of Euclidean distances using *Heterodinium* (W) as target.

Figura 19. Comportamiento estadístico de las distancias Euclidiana utilizando *Heterodinium* (W) como imagen objetivo.

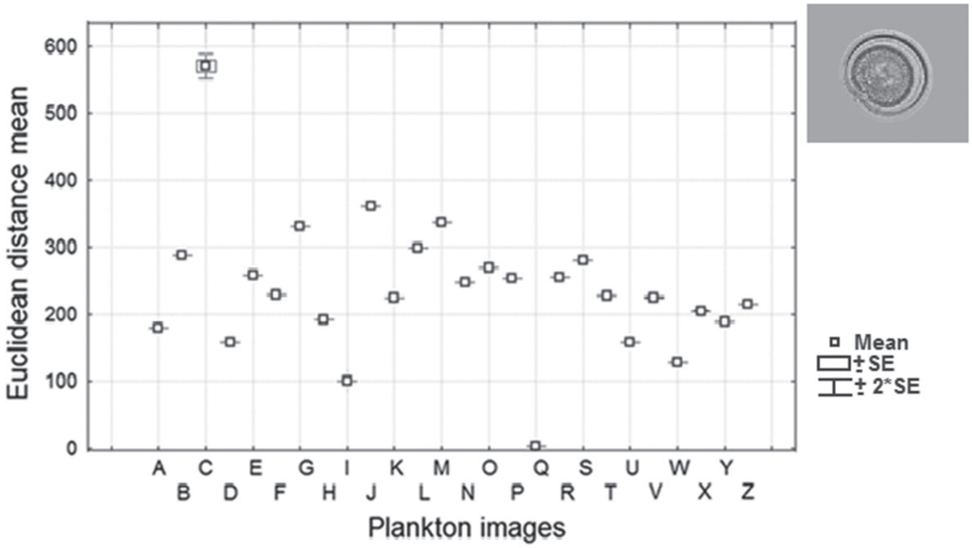

Figure 20.Statistical behavior of Euclidean distances using *Diplopsalopsis orbicularis* (Q) as target.

Figura 20. Comportamiento estadístico de las distancias Euclidiana utilizando *Diplopsalopsis orbicularis* (Q) como imagen objetivo.

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