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An evolving spatio-temporal approach for gender and age group classification with Spiking Neural Networks

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Abstract This research study proposes a novel method of inter-related problems in face recognition using the NeuCube neuromorphic computational platform. We investigated age classification and gender recognition. The well-known FG-NET and MORPH Album 2 image gallery were used and anthropometric features were extracted from landmark points on the face. The landmarks were pre-processed with the procrustes algorithm before feature extraction was performed. The Weka machine learning workbench was used to compare the performance of traditional techniques such as the K nearest neighbor (Knn) and Multi-LayerPerceptron (MLP) with NeuCube. Our empirical results show that NeuCube performed consistently better across both problem types that we investigated.

Keywords Anthropometric model · Age group classification · Gender classification · Spiking neural networks

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1 Introduction

Aging is a slow process and its effects are visible only after a few years. But in spite of being slow, it remains a spatio-temporal phenomenon. The facial features of a person can be considered as a subspace and the aging over the years of this subspace is in turn a temporal process. It would be very useful to incorporate the temporal as well as spatial patterns in aging data as important components in classification. The raw data which has been used in this study is from (FG-NET) and MORPH image galleries. Age group classification and gender recognition have important applications for business managers and law enforcement agencies. In Human Computer Interaction (HCI) gender recognition can be used to make it more amenable to both genders. For example, it enables a computer to address a user by their correct title, Mr or Mrs, as the case may be. Automatic gender recognition facilitates better interaction with humans as well as saves keystrokes in filling up forms. In Surveillance systems, a gender specific physical locality can be concentrated upon, thereby reducing the area under observation and making the whole system more efficient. It could also assign higher threat levels to a specified gender location. In content based systems, indexing and searching can be greatly facilitated. For example, today a plethora of digital videos and photographs are produced. Their gender based indexing and searching can be easily carried out. It will also reduce the search effort by limiting it to a particular gender, thereby making it more efficient. The same applies to Biometrics. The automatic collection of demographic data for statistical purposes will be facilitated if the gender can be automatically recognised.

Age group classification (Kwon and da Vitoria Lobo 1999; Horng et al. 2001; Lanitis et al. 2004; Gunay and Nabiyev 2008; Wang et al. 2009, 2011; Thukral et al. 2012;

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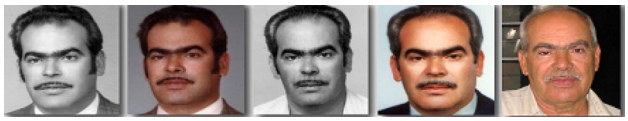


Fig. 1 Same individual at different ages (FG-NET 2002)

Fig. 2 Same individual at different ages from MORPH database (Ricanek Jr and Tesafaye 2006)

Liu et al. 2015) and gender recognition (Guo and Mu 2011; Levi and Hassner 2015) is also an area of research that is receiving a lot of attention due to advances in the field of biometrics (Guo and Mu 2011; Jain et al. 2016; Liu et al. 2015; Ramanathan and Chellappa 2006). There are a number of challenges in making an effective age group classification and gender recognition system, which include: pose, illumination, face expression, occlusions and aging effects. It is challenging to address all of them simultaneously, because if one error is removed then another crops up. We have adopted the approach of using Anthropometric features (Ramanathan and Chellappa 2006) which eliminates some of these problems. This model is based on geometrical ratios and distances of fixed number of fiducial landmarks, which in our case corresponds to 68 landmark points on the face. Since the Anthropometric model uses geometrical distances it is not affected by texture information, illumination and intensity levels. Problems caused by occlusions such as moustaches or spectacles are also eliminated as the distance between features will remain unchanged even if such occlusions occur. However, different poses could create problems (Alvi and Pears 2015a, b, c, 2016). We mitigate the effects of this problem by finding an average of all faces and then warping all images to that image with the help of the procrustes algorithm (Cootes et al. 1999). This allow us to concentrate on effects due to aging. Aging not only changes texture, but also alters geometrical ratios and distance between landmark points. However, such changes over time follow a definite pattern. Thus, our main research hypothesis is that our anthropometric model would provide a realistic basis for studying the effects of aging due to change in geometry of the face (Figs. 1, 2).

This Research focuses on designing a novel framework for age group classification and gender recognition. We use an Anthropometric model for feature extraction and extract seven different indexes. These indexes consist of different distances and geometrical ratios of face features. After extracting features we convert the data into a discrete spike train. We use the AER encoding method to discretize the continuous signal. This encoding method was applied successfully for the artificial retina sensor (Hechenbichler and Schliep 2004). We initialize the NeuCube by using the Small World rule (Hechenbichler and Schliep 2004). At unsupervised training stage we used the STDP rule (Hechenbichler and Schliep 2004). The dynamic evolving Spike Neural Networks (deSNN) is used here as an output classifier. Our choice of the NeuCube platform was influenced by its outstanding success that it has achieved on spatio-temporal classification problems in many diverse (Kasabov et al. 2016; Dhoble et al. 2012; Kasabov et al. 2013; Kasabov 2014; Sengupta et al. 2015; Kasabov 2007). All such studies employing NeuCube have been on data that exhibit a relatively fast pace of temporal changes. However in the aging domain that this research is based on, the speed of changes are much smaller, on the order of months to years rather than hours to seconds, and hence it will be interesting to investigate whether the success of NeuCube can be replicated in such a slow-changing temporal environment. Our empirical results indicate that NeuCube captures temporal patterns well in this domain as well, as its classification accuracy was significantly better than with classical methods such as the K Nearest Neighbor(KNN), Multi Layer Perceptron (MLP) and Naive Bayes classifiers.

2 Literature review

Kwon and da Vitoria Lobo (1999) proposed a classification approach based on age that identifies the age group of given face images. It is based on the anthropometry of the face and the density of its face wrinkles. They considered three age groups in their study. These groups were infants, young adults and senior adults. They also observed that the lower and upper halves of faces grow at different rates during the early formative years.

Lanitis et al. (1999) also used Active Appearance Models (AAM). Lanitis et al used a statistical face model for studying the age estimation problem. AAM parameters were extracted from facial images which were marked with 68 points. A Genetic Algorithm was then applied to build and optimize an aging function.

Geng et al. (2007) worked on the assumption that similar faces age in similar ways across a population. He introduced the method of Aging pattern Subspace (AGES) for modelling aging across time. Geng et al constructed a representative subspace by utilizing a sequence of images of a given individuals face sorted in chronological order. Thereafter, minimum reconstruction error was achieved by

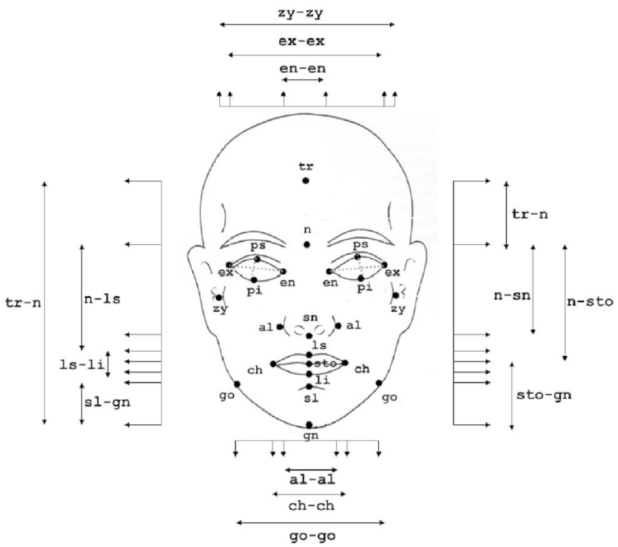
projecting the unseen face image into its proper aging subspace, thus making it possible to determine the age of the image from its aging pattern.

Yan et al. (2008) introduced a method which developed the concept of coordinate patches and Gaussian Mixture Models (GMMs) which were used to estimate facial ages. In their method, the face image of an individual is encoded as a group of overlapped spatially fexible patches (SFPs). Local features are then extracted by a 2D discrete cosine transform (DCT). The patches are used for integration of local features and coordinate information. The extracted SFPs are then modelled with Gaussian Mixture Models (GMMs). The model produced was used to estimate age of a person by comparing the sum of likelihoods from total spatially fexible patches (SFPs) of an hypothetical age.

Guo et al. (2008) designed a localized regression classifier to learn the aging function. The concept of manifold learning was used for age estimation. Fu and Huang (2008) also used manifold learning as well. A set of age separated images were taken and a low dimensional manifold was developed from it. Linear and quadratic regression functions were applied on the low dimensional feature vectors from the respective manifolds.

Face anthropometry is a science of measuring sizes and proportions on human faces. It is found that it can play an important role in developing facial aging models. These sizes and ratios provide a quantitative description of the craniofacial complex at different ages. This provides numerous options for learning based approaches. These approaches are developed to characterize facial aging. Face anthropometric studies take measurements between key landmarks on human faces at different ages. These ratios have played a critical role in surgical procedures employed on the faces of growing children (Farkas and Munro 1987).

Farkas (1994) provides a comprehensive overview of face anthropometry and also describes its many significant applications. He has taken 57 selected landmarks on human face that are spread across 6 6 regions in the craniofacial complex (head, face, orbits, nose, lips and mouth, ear). The facial measurements are of of three kinds: (1) projective measurements (shortest distance between two landmarks) (2) tangential measurements (distance between two landmarks measured along the skin surface) (3) angular measurements. Figure 3 illustrates the kind of data that is collected in face anthropometric studies and further illustrates the different fiducial features across which such data is collected. Since age-based anthropometric data was not available, they prepared it by extracting facial features from passport database. The data was grouped into five age groups, namely 21–30, 31–40, 41–50, 51–60 and 61–70 years. Such data was found to be effective in characterizing facial growth based on age, gender, ethnicity etc. It could also characterise instances when individuals gain or lose



- Facial index $(\frac{n-gn}{zy-zy})$
- Mandibular index $(\frac{sto-gn}{go-go})$
- Intercantal index $(\frac{en-en}{ex-ex})$
- Orbital width index $(\frac{ex-en}{en-en})$
- Eye fissure index $(\frac{ps-pi}{ex-en})$
- Vermilion height index $(\frac{ls-sto}{sto-li})$
- Mouth Face width index $(\frac{ch-ch}{zy-zy})$

Fig. 3 Anthropometric model and seven features (Farkas 1994)

weight. Thus it describes the process of transforming facial appearances with age progression (Farkas 1994).

Biswas et al. (2008) proposed that there is coherency in facial feature drifts across ages. The degree of drift was used as a measure to perform face verification across ages. The assumption was that facial feature drifts observed in images that are age separated follows a definite coherent drift pattern. It was also observed that the same might not be true for age separated face images of two different individuals. Biswas et al suggested that since fiducially extracted features on the outer contour tends to be very sensitive to head pose variations, a suitable pose correction mechanism had to be put in place.

Ramanathan and Chellappa (2006) used eight ratios of distance measures to model age progression in young individuals, ranging in age from 0 to 18 years. These ratios were used to estimate an individual's appearance across time and to perform face recognition across age progression. They experimented with a database of 233 images of 109 individuals, partially collected from the FG-NET aging database and partially from a private gallery of images. Improvements in rank 1 accuracy of 8% (without age prediction) to 15% (with age transformation) was reported.

Liu et al. (2015) proposed a multistage learning system calling it Grouping Estimation Fusion (GEF). It addresses three research issues: age grouping, age estimation and decision fusion for finalizing age estimation. Global and local features are extracted and different groupings are created. A pipelined approach is used, whereby the output of each stage is fed as input to the next stage. The author has proposed six fusion schemes (i.e., intra-system fusion, inter- system fusion, intra-inter fusion, inter-intra fusion, maximum- diversity fusion, and composite fusion) are developed and compared. The performance of the GEF system is evaluated on FG-NET and MORPH databases.

3 Methodology

An Anthropometric model was used in our study. A set of landmarks (a total of 68) was taken on each face, and distances between landmarks as well as ratios between distances were taken for constructing fiducial features. We used 7 such features on the face. The details of the model are given below. Since the images in the database are not of the same size, we applied procrustes to align them to a fixed size. This size was determined by averaging all the images in the database. The final feature determination was done after application of procrustes on landmark coordinates. These features were then fed into NeuCube. NeuCube, featuring a spiking neural network architecture that was successfully used in spatio-temporal modelling in brain data applications (Kasabov 2012, 2014; Kasabov et al. 2014, 2015; Tu et al. 2014). In contrast to brain data signals obtained through the use of devices such as EEG where time length between observations spans seconds, the corresponding time length in facial aging spans years, thus making it an interesting experiment to test the efficacy of NeuCube's spatio-temporal modelling capability in an environment of much coarser time granularity. A block diagram of NeuCube's architecture is shown in Fig. 4. NeuCube consists of three major components: an input encoding module, a three-dimensional Spiking Neural Network Cube (SNNc) and an output dynamic evolving spike neural network (deSNN) classifier (Kasabov 2012). In the first stage we adjust the connection weights in spiking SNNc to learn spatio temporal patterns embedded in the data. In the second stage, supervised learning is carried out.

Overall, the modeling process consists of data encoding, SNNc initialization, unsupervised training of the SNNc and finally supervised training of the classifier. The experiments were performed with CPU of Intel Core i7-2640 M Processor 2.8GHz, Memory of 8 GB, Windows 7 Professional (64 bit) and MatLab (64 bit) R2013a.

3.1 Data encoding

In the aging problem feature data is in the form of real values, and hence needs to be discertized into spike trains. The Address Event Representation (AER) encoding method is used for this purpose. This encoding method was applied successfully for the artificial retina sensor (Hechenbichler and Schliep 2004; Schliebs et al. 2012). We obtain both positive and negative spike trains for encoding. Positive spikes accompany an increase in feature value, whereas a negative spike occurs when the feature value has decreased.

3.2 NeuCube (ST) initialization

We initialize the SNNc by the following rule. Each neuron in the SNNc is connected to its nearby neurons which are within a distance d, where d equals the longest distance between any pair of neurons in the SNNc multiplied by a parameter r. The initial weights are set with r set at random in the range [−1, 1]. We randomly select 80% of the connection weights to be positive and the remaining 20% to be negative in the cube initialization process. The actual proportion of positive to negative connections will change

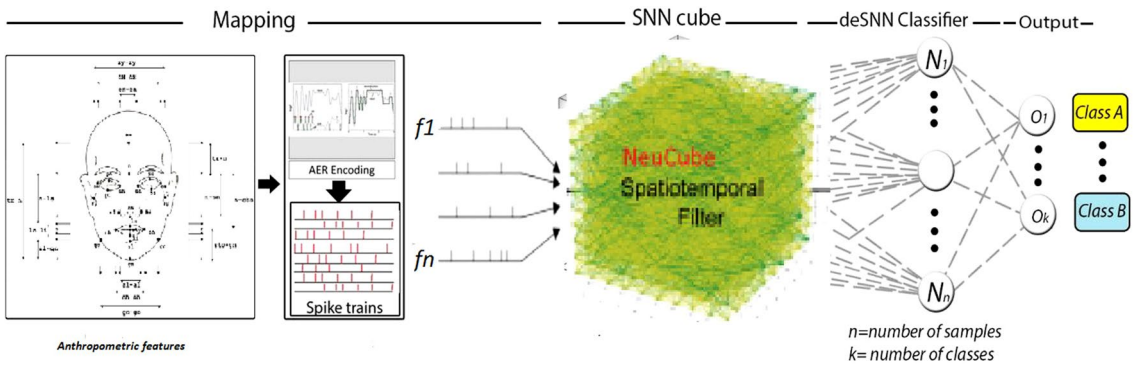


Fig. 4 Schematic representation of the NeuCube-based methodology for mapping, learning, visualisation and classification of FG-NET DATA

continuously due to weight propagation that occurs when data is processed by the cube.

3.3 Training stage I

This stage deals with Unsupervised Reservoir Training. It encodes hidden spatio-temporal relationships from the input data into neuronal connection weights. According to Hebbian learning rule, if the interaction between two neurons persists, then the connection between them will be strengthened. We train the SNNc using the STDP learning rule (Song et al. 2000): if neuron j fires before neuron i, then the connection weight from neuron j to neuron i will increase, otherwise the connection from neuron i to neuron j will decrease. This ensures that the time signal inherent in the input spiking trains will be captured by the neuron firing state and manifest as asymmetrical connection weights in the SNNc.

In the SNNc, when a neuron fires, it emits a spike and then its potential gradually reduces over time to reach a zero value. Each neuron connecting to this firing neuron will receive a spike. Because of the emitted spike the potential of each neighboring neuron will increase in proportion to its connection weight to the current firing neuron. The potential of each neuron has a small, constant rate of leakage over time until it reduces to 0. After learning, the connection weights in the SNNc encode temporal relationships from the input spatio-temporal data (Tu et al. 2014).

3.4 Training stage II

In this stage, supervised classifier training is carried out. The deSNN (Dhoble et al. 2012; Kasabov et al. 2013; Kasabov 2014) is used here as an output classifier, because deSNN is computationally efficient and emphasizes the importance of the first spike, which has also been observed in biological systems.

Once the NeuCube(ST) (Kasabov 2014) is trained, all connection weights in the SNNc and in the output classification layer are established. For a given new sample without any class label information, the trained NeuCube can be used to predict its class label. For the deSNN classifier, there are two algorithms that can be used to determine the class label of the new sample (Dhoble et al. 2012; Kasabov et al. 2013; Schliebs and Kasabov 2013; Kasabov 2014). The deSNN classifier uses one of two algorithms to determine the class label of the new sample. One is (Dhoble et al. 2012; Kasabov et al. 2013; Kasabov 2014) and other is deSNNm (Dhoble et al. 2012; Kasabov et al. 2013; Kasabov 2014). We have used the deSNNs algorithm in this work.

4 Empirical results of age group classification

Experiments were performed on the publicly available FG-NET (FG-NET 2002) and MORPH Album 2 (the largest publicly available face aging dataset) (Ricanek Jr and Tesafaye 2006), both of which are used for benchmarking new methods. The lack of a large face aging database until recently limited research on age group classification. There are two desired attributes of a face aging database: (1) large number of subjects, and (2) large number of face images per subject captured at many different ages (Li et al. 2011). In addition, it is desired that these images should not have large variations in pose, expression, and illumination. The MORPH dataset has a large number of subjects while FGNET database has a large number of images. The MORPH dataset contains about 55,000 face images from 13,000 different people.

In all experiments, the size of the SNNc is 1000 neurons, a relatively simple $10 \times 10 \times 10$ cube. It is trained and tested using a leave one out method. Firstly we converted the data into discrete spike trains using the AER encoding method to discretize the continuous signal, following the example of the silicon retina (Hechenbichler and Schliep 2004). The deSNN classifier mentioned previously is used here as an output classifier because deSNN is computationally efficient and emphasizes the importance of the first spike which has been observed to be significant in biological vision systems. We conducted experiments to compare traditional modeling methods (Knn, Niave Bayes and MLP) and our pro-posed method for age group classification.

We designed three experiments for these baseline algorithms. Note that for these baseline algorithms, the time length of training samples and testing samples have to be the same as these methods cannot tolerate different lengths of feature vectors for training and testing. Table 3 shows clearly that the classification achieved with NeuCube significantly outperformed the other techniques. The results clearly indicate that NeuCube with its spatio temporal capability can capture the aging effects more effectively than classical classifiers that do not explicity take into account the time dimension in the data.

Since evolving system data machines (eSTDM) model relationships both between and within spatio-temporal data, even a small amount of input data will be able to trigger the spiking activities in SNNc, giving rise to a more accurate pattern (class) recognition rate from image data.

In order to assess generality of our models on different types of databases, we used MORPH Album 2 (the largest publicly available face aging dataset) database. We annotated the fiducial landmarks with Stasm, a method based on Active shape Models (Milborrow and Nicolls 2014) (Fig. 5).

Fig. 5 Fiducial landmark detection results from MORPH database. *Blue points* represent the 68 landmark points

4.1 Age group classification with FG-NET

For this experiment we distributed the FG-NET Database into three age groups, the first being the 0–3 age group, the second grouping as 4–16 and the final one as 17–69. We set the sample size to span 5 divisions of time within each age group. We then chose 30 samples from each group, thus enabling 150 images to be selected for each group. For age group 1 the 150 images that were chosen were assigned as class 1. Similarly, we chose 150 images from age group 2 and assigned them as class 2 and did the same for age group 3. For each of the images we take 7 features. Each sample provides a 5×7 matrix with each having 7 features. In all there are 90 samples. The leave-one-person-out testing strategy is used for the FG-NET database. For comparative purposes we used the same testing strategy as in Liu et al. (2015).

The data was then fed to NeuCube and Weka. The results of this experiment are given below.

We benchmarked our NeuCube results against classical classifiers such as the k nearest neigbor, Multi Layer Perceptron and Naive Bayes.

Table 1 shows that NeuCube showed outperformed all of the general purpose classifiers, with the k nearest neighbor performing best amongst them.

Table 2 shows that Age Group Classification using a NeuCube eSTDM for each age group separately for FG-NET database.

Table 3 shows that the purpose-built age classifiers performed better than their general purpose counterparts. However, a substantial gap still exists between them and NeuCube.

4.2 Age group classification with MORPH

We randomly selected a subset of about 21,000 faces from MORPH database that contain black and white, Female and Male faces. Each sample provided a 5×7 matrix with each having 7 features. Our setting of the experiment is similar to that of Liu et al. (2015) and Guo and Mu (2011). We divide data into three subsets, S1, S2 and S3. We used S1 for training and tested it with W/S1. Then we used S2 for training and tested with W/S2. Finally, we averaged the two results to obtain an overall result.

Table 1 Age group classification using a NeuCube eSTDM in comparison to traditional classifiers: Knn, MLP, NB

Measure	NeuCube	MLP	knn	NaiveBayes
Accuracy (%)	98	80	91.1	66.7

Tables 4, 5 and 6 mirror the results for the FGNET database, once again underlining the superior performance of NeuCube.

4.2.1 Discussion

In Figs. 6, 7 and 8, blue lines represent positive connections (i.e. those with positive weights) while red lines represent negative connections (those with negative weights). The colour of a neuron signifies its connectivity; the brighter the color, the larger is the size of its neighborhood. The thickness of a line denotes the intensity of a connection between a pair of given neurons. Thus a thick blue line indicates a strong positive connection, while a thin blue line also represents a positive connection but one with a lesser strength.

Figures 6, 7 and 8 show that different age group activate different parts of the cube, as indicated by their connectivity.

Figures 6 shows that in age group (0–3), the Facial, Intercantal and Orbital width indexes have the strongest level of expression when compared to the two other age groups as they have stronger positive connections when compared to their counterparts in Figs. 7 and 8. Changes in variables in a Spiking Neural Network result in increased spiking activity which in turn spawns positive connections. Thus we can conclude that Cranofacial growth in age group (0–3) occurs at a faster rate than with other two age groups.

Figure 7 shows that in age group (4–16) that there is strong connection strength in the Eye fissure and Mandibular index regions due to the presence of thick blue lines. Mandibular and Eye fissure indexes are associated with the eye and chin ratios. This suggests that most changes in the face occur in these features at age group (4–16).

Figure 8 shows that in age group (17–69) most of the strong connections seem to occur in the Orbital width, Intercantal, Mandibular and Facial index regions. Even though three of these features, namely the Facial, Intercantal and Orbital indexes, are also expressed in age goup (0–3), the levels of expression is less than that for age group (0–3). Thus we can conclude that while most changes in age group (17–69) occur in these indexes, the rate of change is slower with age goup (0–3).

Our comparative analysis shows that in all three age groups the Mandibular and Intercantal indexes are active

Table 2 Age group classification using a NeuCube eSTDM for each age group separately

Age groups	0–3	4–15	16–69
Accuracy (%)	100.00	96.00	98.00

Table 3 Comparative results of age group classification with state-of-the-art age group classifiers

Models	Classification (%)
NeuCube	98
Liu et al. (2015)	93.5
Sai et al. (2015)	90

Table 4 Results of age group classification using a NeuCube eSTDM in comparison to traditional classifiers: SVM, MLP, NB

Measure	NeuCube	MLP	Knn	NaiveBayes
Accuracy (%)	95.00	82.30	89.03	67.60

Table 5 Age Group Classification using a NeuCube eSTDM for each age group separately

Age groups	15–29	30–49	50–77
Accuracy (%)	98.00	91.00	96.00

Table 6 Comparative results of age group classification with Morph Album 2

Models	Classification (%)
NeuCube	95
Liu et al. (2015)	92.6
Sai et al. (2015)	71.2

as they are associated with strong spiking activity. The Eye fissure index creates strong spikes during age group (4–19) and (17–69). The Vermilion height index shows weak connections and a low level of spike activity in age groups (0–3) and (17–69). However, the Vermilion index shows a medium level of spike activity and strong connection weights in age grouping (4–16).

We observe that there is a clear shift away from the Facial, Intercantal, Orbital width and Mouth Face width indexes as markers for the age group (0–3) to Mandibular and Fissure indexes for age group (4–16). The fact that different indexes are prominent at different age groups suggests that NeuCube has succeeded in capturing the aging process. This is useful on two different accounts. First, it provides solid evidence that NeuCube is capturing not just the temporal but also spatial signals in the data. Second, from the viewpoint of aging research it provides a useful insight into the changes that take place in the face over time and enables interested researchers into building more useful age estimation models. It also provides the potential to simulate future changes in a person's face over time (Tables 7, 8, 9).

We conclude this section by observing that NeuCube not only outperformed its rivals across both databases in terms of classification accuracy but also yielded useful insights into the aging process.

5 Empirical results of gender recognition

5.1 Gender recognition with FG-NET

For this experiment we use the FG-NET Database. We model Gender recognition as a two-class classification problem. We assign the gender label through a visual inspection of the data, with class 1 as male and class 2 as female. We also used the classical classifiers from Weka as in the first experiment for comparative analysis. For each of the images we take 7 features. Each sample provides a 5 $\times$ 7 matrix, ie 5 images, each having 7 features. In all there are 172 samples. The leave-one-person-out testing strategy is used for FG-NET. Table 10 shows the results of the gender recognition classification process.

Tables 10 and 11 show clearly that NeuCube has better classification performance when compared to all of its rivals.

5.2 Gender recognition with FG-NET in a younger age group (0–18)

For this experiment we use the FG-NET Database. For each of the images we take 7 features. Each sample provides a 5 $\times$ 7 matrix ie 5 images, with each having 7 features. In all there are 120 samples. The leave-one-person-out testing strategy was used for FG-NET. Table 12 shows results of gender recognition in the younger age group.

5.3 Gender recognition with MORPH

For this experiment we use the MORPH Database. We model Gender recognition as a two-class classification problem. We use the same testing strategy as used in Guo and Mu (2011) and Liu et al. (2015). This data is then fed into the NeuCube. We use the same classical classifiers from Weka as we did in the first experiment for comparative analysis. For each of the images we take 7 features.

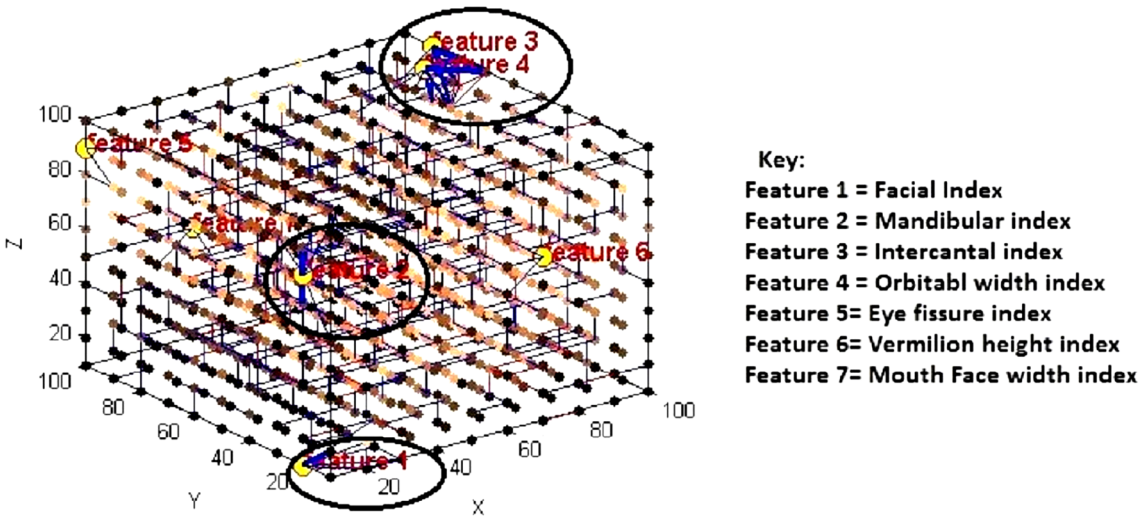


Fig. 6 Age group (0–3). The size of the SNNc is controlled by three parameters: $n_x, n_y, andz_n$, representing the neuron numbers along x, y and z direction. And the total neuron number in the cube is $N = n_x \times n_y \times n_z$.A SNNc of 1000 ($10 \times 10 \times 10$) neurons are shown in above aging model

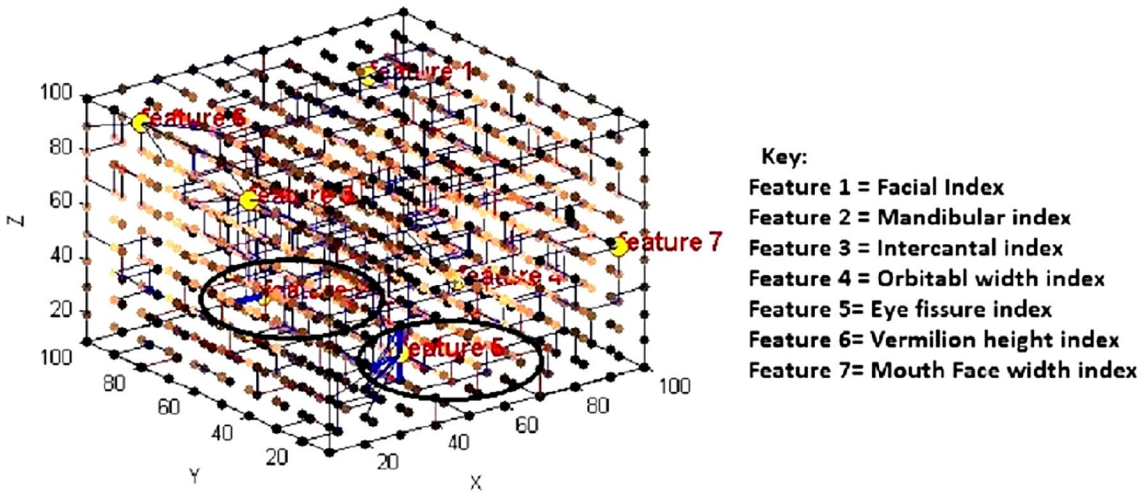


Fig. 7 Age group (4–16)

Each sample provides a 5×7 matrix ie 5 images, with each having 7 features. In all there are 3378 samples.

Tables 13 and 14 show clearly that NeuCube has better classification performance when compared to all of its rivals.

5.4 Gender recognition with MORPH in a younger age group (16–20)

In all there are 420 samples that we use for this experiment. Each sample provides a 5×7 matrix with each image having 7 features. We use the same testing strategy as used in Guo and Mu (2011) and Liu et al. (2015). Table 15 shows results of gender recognition in the younger age groups.

It was observed that the gender recognition classification achieved with NeuCube was better than with other traditional techniques for the younger age groups.

5.4.1 Discussion

In Figs. 9 and 10, line colour, thickness and coloring of neurons have similar meaning to that described above.

By visualization of the cube in Fig. 9 we can see that the Intercantal, Vermilion height, Eye fissure and Mouth Face Width indexes have strong positive connections. However, the Mandibular, Facial and orbital indexes show weak connections caused by less spiking activity.

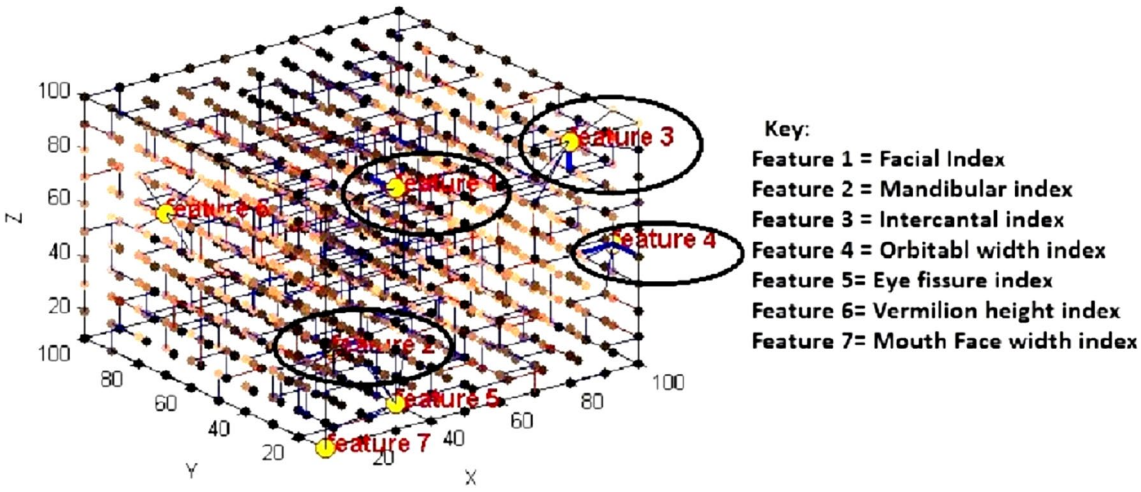


Fig. 8 Age group (17–69)

Table 7 Feature profile for age group (0–3)

Features	Influence level	Connections
Facial	High	Strong
Mandibular	High	Strong
Intercantal	High	Strong
Orbital width	High	Strong
Eye fissure	Low	Weak
Vermilion height	Low	low
Mouth Face Width	Medium	strong

Table 8 Feature profile for age group (4–16)

Features	Influence level	Relationship
Facial	Low	Weak
Mandibular	High	Strong
Intercantal	Medium	Weak
Orbital width	Low	Weak
Eye fissure	High	Strong
Vermilion height	Medium	Weak
Mouth Face Width	Low	Weak

Table 9 Feature profile for age group (17–69)

Features	Influence level	Relationship
Facial	Medium	Weak
Mandibular	High	Strong
Intercantal	Medium	Strong
Orbital width	High	Strong
Eye fissure	High	Weak
Vermilion height	Low	Weak
Mouth Face Width	Low	Weak

In Fig. 10 we see that all features generate high spikes and stronger connections except for the Vermilion height index. This is typical for the female specimens in the data sample.

By conducting a comparative analysis we observe that in both genders that the Intercantal, Eye Fissure and Mouth Face Width indexes show strong positive connections, implying that more changes would occur in eyes, mouth and bone structure between eyes.

The Facial, Mandibular, Orbital width and Vermilion height indexes behave differently across the genders, implying that a gender aging pattern exists. This further validates the point that gender also effects the face recognition process. Therefore, it is recommended that gender-specific aging models be built for age invariant face recognition.

By visualization we can also see another interesting effect, facial index, mandibular index, intercantal index and orbital index show strong connections for female gender as compared to male gender. It may be concluded that female gender ages more quickly as compared to male gender.

In these experiments we can see that the NeuCube has the capability of providing better accuracy as compared

Table 10 Gender classification on FG-NET

Measure	NeuCube	MLP	KNN	NaiveBayes
Accuracy (%)	95.00	76.10	83.00	62.79

Table 11 Age group classification on FG-NET

Models	Classification (%)
NeuCube	95
Guo and Mu (2011)	87.20

Table 12 Gender Classification for younger age group (0–18)

Measure	NeuCube	MLP	KNN	NaiveBayes
Accuracy (%)	85.00	72.60	70.80	67.3

Table 13 Results of gender classification using a NeuCube eSTDM in comparison with traditional techniques: Knn, MLP, NB

Measure	NeuCube	MLP	KNN	NaiveBayes
Accuracy (%)	99.00	76.30	88.00	66.00

Table 14 Comparative results of age group classification with FG-NET database

Models	Classification (%)
NeuCube	99
Guo and Mu (2011)	98.20

Table 15 Results of Gender Classification at a younger age group (16–20) using a NeuCube eSTDM in comparison with traditional techniques: KNN, MLP, NB

Measure	NeuCube	MLP	KNN	NaiveBayes
Accuracy (%)	87.0	68.3	79.3	63.8

to the traditional methods. Its main strength lies in three dimensional connections and their weights and the ability of learning spatio temporal aging process (Tables 16, 17).

6 Conclusion

In this paper we researched two inter-related problems in face recognition using the NeuCube computational platform. The well-known FG-Net and Morph image galleries were used and Anthropometric features were extracted from landmark points on the face. These features enabled learning of spatio temporal relationships. The Weka machine learning workbench was used to compare the performance of traditional classifiers such as the K nearest neighbor (Knn), Multi-LayerPerceptron (MLP) and Naive Bayes with NeuCube. This research has revealed that NeuCube has the capability of giving better performance for gender recognition and age group classification because it has the capacity to learn both spatial and temporal relationships simultaneously.

Our empirical results show that NeuCube performed consistently better across both problem types that we investigated. We explored the temporal relationships between different Anthropometric features. The aging process causes significant alterations on the human face, thus affecting the long term performance of face authentication systems. Our research also revealed that different Fiducial markers are prominent at different age groups, thus offering the possibility of estimating aging effects for future points in a given person's timeline. However, for age simulation to be successful such markers may need to be combined with other person-specific information such as lifestyle and environment variables that could also impact on shaping a person's facial profile over time.

One direction that can be explored is to construct NeuCube aging models for each feature separately and then fuse the different models to build a composite model of the

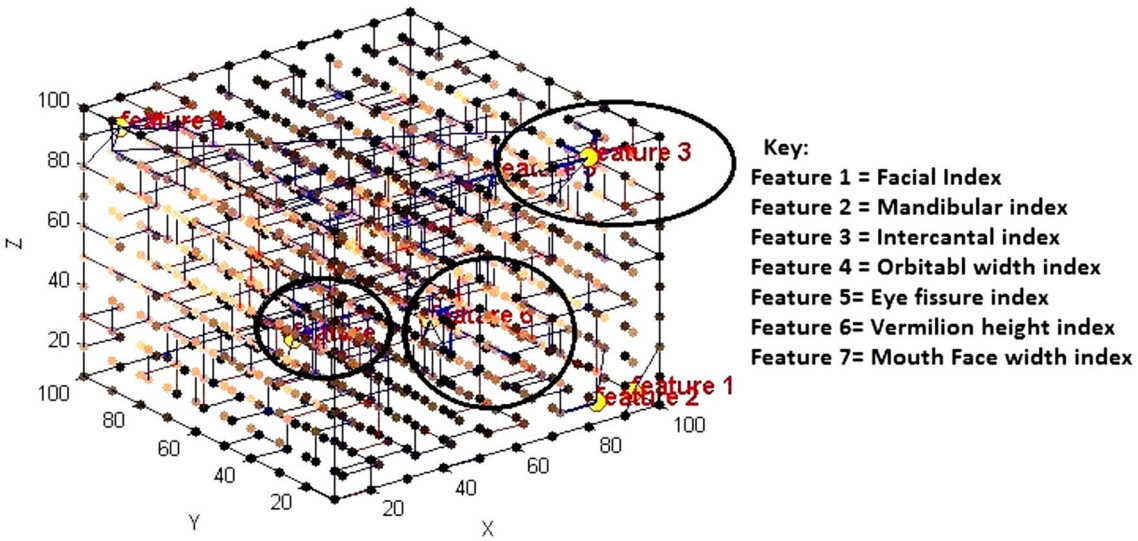


Fig. 9 Male

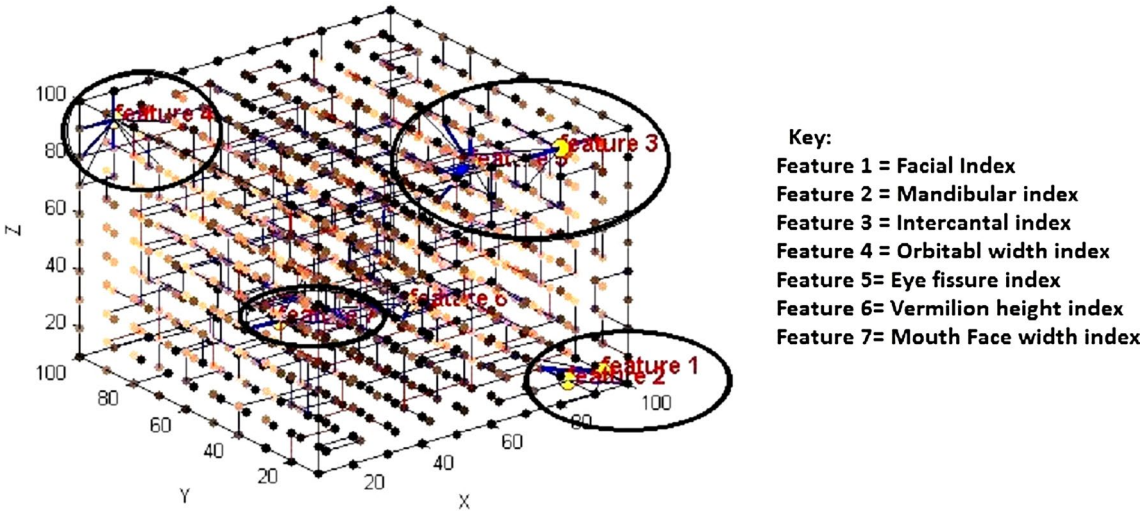


Fig. 10 Female

Table 16 Feature profile (male)

Features	Influence level	Connections
Facial	Low	Weak
Mandibular	Low	Weak
Intercantal	High	Strong
Orbital width	Low	Weak
Eye fissure	High	Strong
Vermilion height	High	Strong
Mouth Face Width	High	strong

Table 17 Feature profile (female)

Features	Influence level	Connections
Facial	High	Strong
Mandibular	High	Strong
Intercantal	High	Strong
Orbital width	High	Strong
Eye fissure	High	Strong
Vermilion height	Low	low
Mouth Face Width	High	strong

simulated face. Modelling each feature separately is attractive as it allows each feature to express its individual contribution to the aging process to the maximum possible extent without interference from the other features. Our future research will explore this approach in depth.

In conclusion we observe that NeuCube provides a good platform for aging research, whether the objective is age estimation or estimating change in facial features over time, thus opening up future research opportunities in these two key areas of aging research.

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