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Automated Sorting of Consumer Image Collections using Face and Peripheral Region Image Classifiers

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Abstract — *An evaluation of techniques and recognition technologies for use in an automatic cataloging tool for consumer image collections is presented. A working implementation of an automatic cataloging tool and user search tools are described. Techniques for combining multiple classifiers derived from face and peripheral regions are discussed. Practical aspects of the requirements for a working in-camera solution are also discussed.*[1].

Index Terms — Image Collections, Digital Camera, Image Processing, Image Sorting and Retrieval, and Person Recognition.

I. Introduction

Digital cameras continue to be one of the CE industry's recent success stories. However as users switch from conventional to digital photography they find themselves with rapidly growing collections of digital images. Few consumers have the time and personal discipline to manually catalog and organize these growing personal image collections.

In this paper we present an evaluation of current state of-the art “person-recognition” technologies which allow us to build an automatic cataloging tool for consumer image collections. The recognition technologies assessed include several means of face recognition, including PCA and DCT-based techniques and a number of color and texture-based analysis tools which allow a persons clothing, hair and other distinctive features to be incorporated into our image cataloging tool.

The tool employs several known image-processing techniques and combines the results of these techniques to provide a novel means of determining similarity ranking between member images of a collection. These techniques have been chosen to minimize the retraining requirements as an image collection grows and to facilitate the merging of smaller image collections into larger meta-collections. These aspects make the system described in this paper particularly suitable for in-camera implementations as will be discussed later.

One of the principle challenges in implementing a workable cataloging system is the ad-hoc nature of consumer images. For example the quality of identified face regions is often poor and unsuitable for conventional face recognition techniques. Through a novel combination of these techniques for analyzing the detected face regions and peripheral regions associated with them our system can provide information related to a person's clothing, hairstyle, pose and appearance. Thus images can be more accurately sorted and browsed.

II. System Overview

We first present an overview of the automated image analysis chain. The same processing steps are employed during the initial training of an image collection, and subsequently when a new image is acquired in order to compare it with previously analyzed images from the collection. These are:

A. Face Detection

The problem of detecting faces in image is well known [1, 2] and will not be discussed in detail in this paper. We have evaluated a number of automatic face detection techniques and the best success rates, in our experience, are obtained from a modified variant of the algorithm described in [2]. However it is worthwhile remarking that 90%+ of the time required by our algorithm is spent in the face detection phase. Thus, although state-of-art face detection algorithms are quite robust and accurate they remain as a final barrier to a full in-camera implementation of the technology described in this paper.

B. Face Region Normalization

After a face region is detected it is generally necessary to try and align and/or resize the region so that it can be subsequently analyzed by standard face recognition tools. The system described in this paper has been restricted to 2-D normalization techniques. This is mainly to reduce the computational requirements of the normalization algorithms with a view to an eventual in-camera implementation.

C. Image Classifiers

We next describe the main image classifiers which are used in our automated image classification system.

1) Face Recognition Classifiers

As we are generally restricted to relatively small subsets of people in a consumer image collection standard recognition algorithms can be employed with a high degree of success. Evaluations are presented of PCA *(principle component analysis)*, ICA *(independent component analysis)*, DCT and wavelet based techniques [3, 4, 5].

2) Clothing Color & Texture Analysis

When browsing for person in a collection of images usually we want to find the person in a specific context, e.g. holiday photos , special events, public appearances, etc. Typically a person will wear the same clothing & hairstyle on a particular occasion. Thus image sorting can be improved by identifying particular items of clothing & jewellery. Note too, that the

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color and texture of clothing is less influenced by light, focus or position than are the results of applying face recognition.

3) Hairstyle Color & Texture Analysis

A color & texture analysis of the hairstyle of a person can further enhance the sorting and retrieval of images. We further remark that the border region between the face and hair regions is more useful for differentiating between people than the bulk texture and color of a person's hair on its own. **Fig 1** illustrates the determined face region *701*, and its associated peripheral regions *702, 703* as used by the main image analysis module which we shall describe shortly.

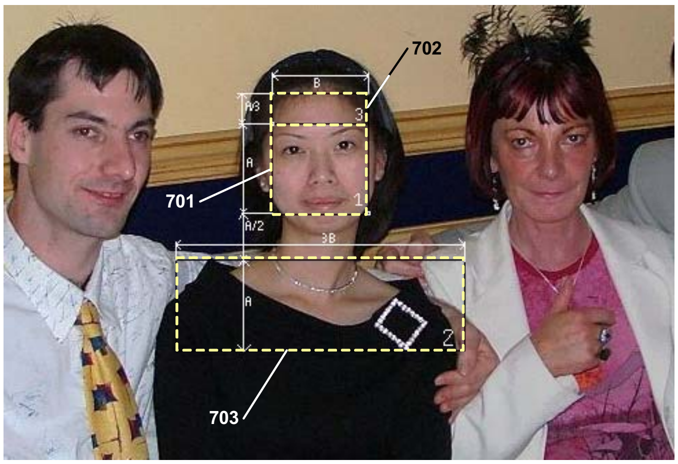

***Fig 1:** A detected face region [701] and associated peripheral regions for hair [702] and top-body clothing [703]*

III. SYSTEM ARCHITECTURE

This is described in ***Fig 2***. A detailed description of the main system components is given in this section.

A. *Training Module*

Before the image sorting & retrieval module can perform its main functionality it is first necessary to initiate a training process on an image collection. To simplify certain implementation aspects we assume that an image collection is a set of images contained within a subdirectory of the file system on a desktop PC. when a user switches into a subdirectory containing images our application loads a data file relating to this image collection and determines: (i) if it was previously trained are there images which have not yet contributed to the training process, and (ii) if the number of such unutilized images indicates that an incremental training process should be initiated. Alternatively, if this image collection data file does not exist the application assumes that this image collection is "untrained" and will automatically initiate a full training process.

Before any image sorting and retrieval can be carried out by our image classification system it is first necessary to initiate a training process on an image collection. In our working implementation we assume that an exemplary image collection is a set of images contained within a subdirectory of the file system on a desktop PC. Thus, when the image classification software is active and a user switches into a subdirectory containing images the software must load this new image collection and determine firstly if there are images which have not contributed to the training process and secondly if the number of such unutilized images warrants a full retraining of the image collection or if, alternatively, an incremental training process can be successfully employed.

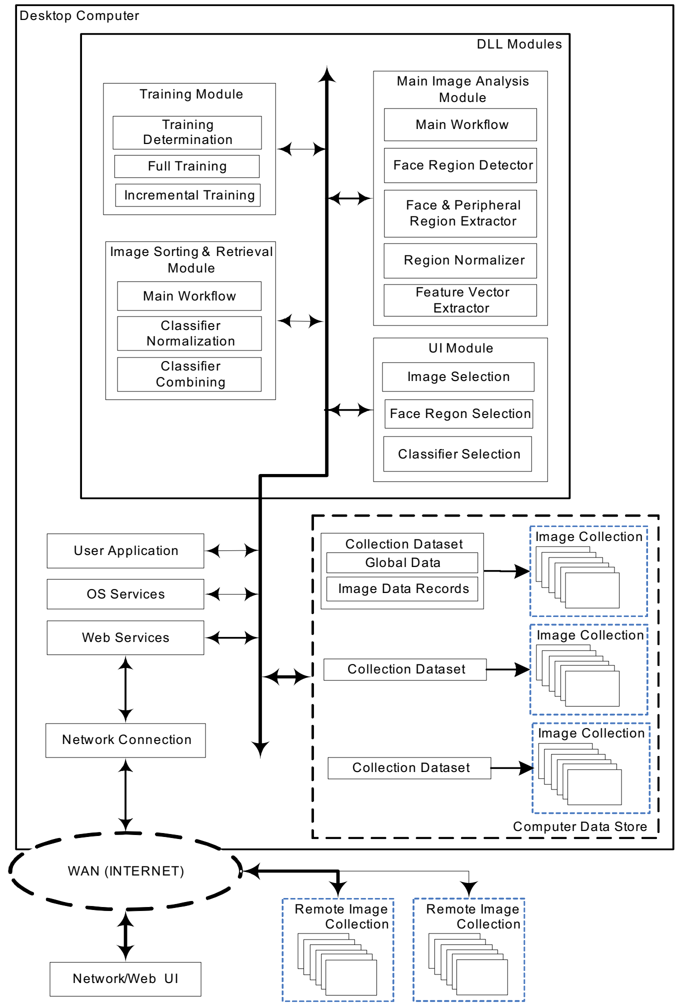

Fig 2: Main System Architecture.

Fig 3 illustrates this process of determining which training method - full, incremental or no training - is to be applied to an image collection; thus, in response to some external user input the training mode determination process first checks if new, unutilized images have been added to the image collection since the last determination of training mode. If no new images have been added, or the number of new images is less than a predetermined threshold value or percentage then no training is required and the training mode determination process may exit.

However, if enough unutilized new images have been added the next step is to determine if incremental training is possible. This decision will depend partly on the nature of the classifiers used in the person recognition process, partly on the number of unutilized images and partly on the number of images and determined face regions in the previously trained image collection.

In our current implementation all of the face and non-face recognition techniques employed can be combined linearly which allows incremental training even for quite large additional subsets of new images which are added to a previously trained main image collection. However this does not preclude the use of alternative face or non-face recognition methods which may not support linear combination, or may only support such combinations over small incremental steps.

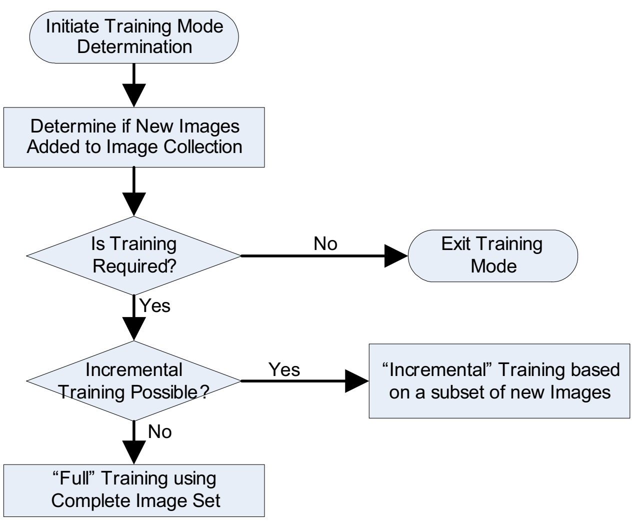

Fig 3: Determination of Training Mode to be Applied.

If it is determined that incremental training is possible then the training mode determination step exits to the incremental training step which is further described in Fig 4(b). Alternatively, if there are too many new images, or the classifiers employed in system are not susceptible to linear combination between image sets then a full retraining must be undertaken. This step is further described in Fig 4(a).

A further advantage of our approach is that the determined facial regions and the normalization process associated with each such region can be re-utilized in subsequent re-training operations. As the automated determination of valid face regions within an image and the normalization of such regions is the most time-consuming part of the training process – typically representing 90-95% of the time required for training a typical image collection - this means that subsequent combining of several image collections into a "super-collection" and re-training of this "super-collection" can be achieved in substantially less time.

1) Full Training Mode Workflow

Once it is determined that and entire image collection must be trained the next step is to load a set of data/memory pointers or file handles which will allow all of the individual images of said collection to be accessed as required; next the main image analysis module is called with the full image collection as an input.

We remark that in full training mode it may not be possible to complete all steps in the feature vector extraction process in the main image analysis module, shown in Fig 4(a), because the relevant basis vector set may not yet be determined; in our implementation this is the case for the Wavelet/PCA classifier method where this step cannot be properly completed until all images have been analyzed. This can be solved in two ways:

(i) the main image analysis module must be called a second time but will only repeat the required classification steps which could not be completed on the first pass; or

(ii) the incomplete feature vector extraction steps must be performed externally to the main image analysis module.

Thus, after applying the main image analysis module, shown in Fig 4(c), the mean wavelet face can be calculated and the PCA basis vector set can subsequently be determined. Following these operations it is now possible to explicitly complete the extraction of the feature vector set for the PCA/Wavelet method of face recognition, or alternatively to call the main image analysis module a second time, with input flags set to skip most of the internal processing steps apart from this step. As both the colour correlogram and DCT face recognition techniques chosen for our implementation use predetermined basis vector sets the feature vectors associated with these classifiers can always be calculated within the main image analysis module.

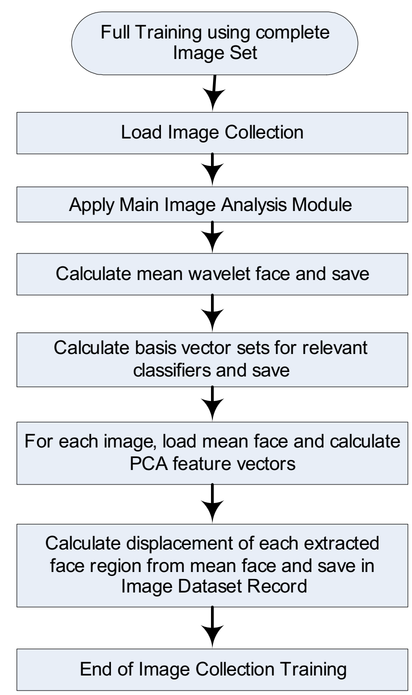

Fig 4(a): Full Training Mode Workflow.

Finally, having determined the feature vectors for PCA we next use these to calculate the vector displacement, in PCA classifier space, of each extracted face region relative to the mean face. This "relative" set of feature vectors is then added to the relevant image data record. Finally we exit the full training module, returning to the calling module.

2) Incremental Training Mode Workflow

Normally an image collection will only need to go through this (automated) full training procedure once. After that initial training it will normally be possible to add and analyze new images using the determined basis vector set for PCA. When a larger subset of new images is added to a collection it will generally be possible to incrementally modify existing basis vector sets by only training the newly added image subset and subsequently modifying the existing location of the mean face and the previously determined basis vector set for PCA/Wavelet face recognition. Fig 4(b) describes this process in detail illustrating the incremental training workflow which allows image subsets to be integrated with a previously trained image collection. This is the normal mode of image collection training.

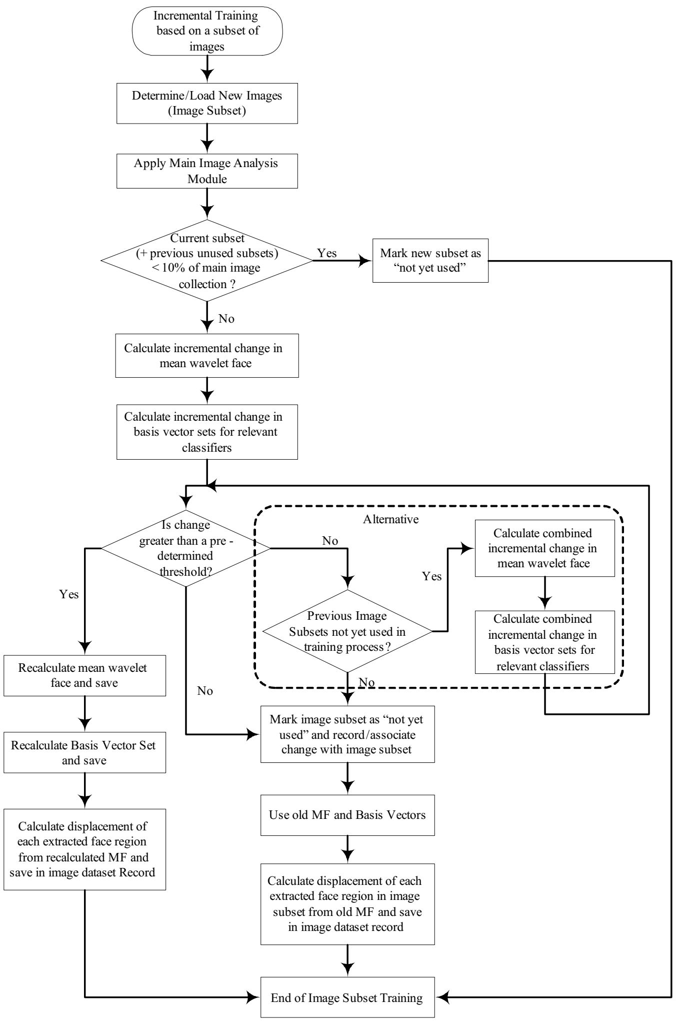

Fig 4(b): Incremental Training Mode Workflow.

It begins by a determination from the workflow of Fig 3 which initiates the incremental training mode. Next a set of data/memory pointers or file handles which will allow all of the individual images of the image subset to be accessed as required is loaded. The main image analysis module is now applied to the loaded image subset, using the existing basis vector sets for extracting feature vectors for each classifier. After the main image analysis module, shown in Fig 4(c), has finished, the incremental change in the mean wavelet face and the PCA basis vector set for the combined image collection (original collection + new subset collection) can now be estimated.

Note that if the size of the new image subset (plus any previous subsets which were marked as "unused for training") is small relative to the size of the main image collection (say < 10%) then these steps may optionally be deferred and the images in the image subset are temporarily marked as "unused for training". Subsequently when a larger set of images is available the incremental training module will take all of these images marked as "unused for training" and perform incremental training using a larger combined image superset. In that case the next step is to calculate the incremental change in the previously determined mean face location which will be produced by combining the new image superset with the previously determined training data. Once the new mean face location is determined the incremental changes in the basis vector set for this classifier should next be determined.

If either incremental change is greater than a predetermined threshold then the mean wavelet face must be recalculated. The relevant basis vector sets must be also be recalculated and finally the actual feature vector sets for each affected classifier must be recalculated for all the determined face regions in each image.

We remark that if the classifiers are chosen, as they are in our working implementation, so that the superposition theorem (linear combination) applies to the classifier space from which a feature vector describing a pattern is derived then it is a simple matter to incrementally adjust the feature vector sets for each image without a need to call the main image analysis module. Note that if it were necessary to call the main image analysis module this would, in turn, require that each image is reloaded and the necessary face & peripheral regions are extracted, normalized and analyzed.

If these incremental changes are less than their predetermined thresholds then the effects of completing incremental training will be minimal and it does not make sense to do so. In this case the current subset is marked as "unused for training" and the determined incremental changes are also recorded in a global collection dataset. In this case the old mean face and basis vector sets are retained and are next used to calculate the feature vectors relative to the old mean face.

In a variation on the above workflow the determining of step can be limited to the current subset (i.e. no account is taken of additional subsets which were not yet used in training) and the additional set of steps marked "alternative" can be used. In this case, if the incremental changes determined from the current subset is below the predetermined threshold then the workflow selects this "alternative". When additional subsets are available these are combined with the current image subset and the combined incremental change in mean face is determined followed by a determination of the combined incremental change in the basis vector set for this classifier. The workflow next returns to the determining step, repeating the previous analysis for the combined image superset comprising the current image subset and any previously unused image subsets. In this manner the incremental training module can reduce the need for retraining except when it will significantly affect the recognition process.

It is also possible to combine previously trained image collections into a "super-collection" comprising of at least two such collections. In this case it is desirable to re-use image collection data which is fixed, i.e. data which is not dependent on the actual set of images. In particular this includes the determined locations of face/peripheral regions within each image and the normalization data pertaining to each such predetermined face/peripheral region. The determination and normalization of such regions is, typically, very time consuming for a consumer image collection taking 90-95% of the time required by the training process. For a collection of several hundred images, with an average size of 3 megapixels, this can take of the order of tens of minutes, whereas the time required by the actual training engines which extract classifier data from the determined face regions will normally require of the order of several seconds per training engine.

B. *Main Image Analysis Module*

This module, hereafter referred to as the *main image analysis module* is used in both training and sorting/retrieval modes of the main system. It handles the actual process of cycling through a set of images and determining, extracting, normalizing and analyzing face regions and associated peripheral regions.

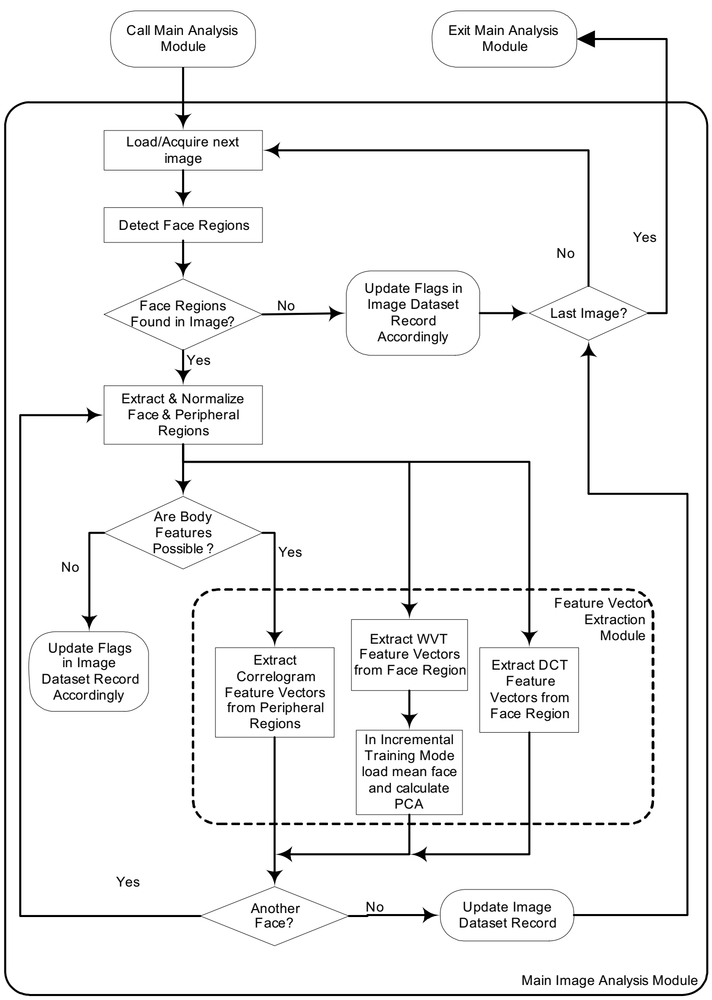

Fig 4(c): Main Image Analysis Module.

It is called from a higher level workflow and, in its normal mode of usage, is passed a set of images which must be analyzed. Where at least one face region is detected this module next extracts and normalizes each detected face region and, where possible, any associated peripheral regions. Finally it determines feature vector sets for a plurality of face and non-face classifiers and records this extracted information in an image dataset record.

C. *Image Sorting & Retrieval Module*

This module calls the *User Interface* module which allows a user to browse images in the current image collection. Once a user has selected a suitable master image the main workflow will determine if there are marked face regions, or if an image was not previously marked it may decide to call the main image analysis module to search for face regions. The user then selects one, or more, face regions and selects the search mode, or classifiers to be used for this search.

Now that the training process for an image collection has been described we must now consider how the image sorting/retrieval module functions.

1) *Image Selection Process*

A selected image will either be a newly selected/acquired image, in which case it must be loaded, selected or acquired and then subjected to face pattern detection followed by a feature vector extraction process which may additionally incorporate pattern region extraction, related peripheral region extraction and region normalization steps. The extracted feature vector will be used for comparing with pre-determined feature vectors obtained from an image collection dataset. Alternatively, if an image is a member of an existing image collection, then the relevant feature vectors will have been previously extracted and it is only necessary to load the previously acquired image and the appropriate image data record and image collection dataset.

2) *Main Image Sorting/Retrieval Process*

This module is initiated by an image selection or acquisition process. It is assumed that when the image sorting/retrieval module is activated it is provided with at least two input parameters providing access to (i) the image to be used for determining the search/sort/classification criteria, and (ii) the image collection dataset against which the search is to be performed. If a data record has not already been determined for the search image the main image analysis module is next applied to it to generate this data record.

The image is next displayed to a user who must make certain selections of the face regions to be used for searching and also of the classifiers to be used in the search. Alternatively, the search criteria may be predetermined through a configuration file and this step may thus be automated. Further discussion of a typical UI interface is given shortly.

After the face and/or peripheral regions to be used in the retrieval process are selected the main retrieval process is initiated by user interaction. This process comprises three main subprocesses each of which is iteratively performed for each classifier which is to be used in the sorting and retrieval process:

(i) Distances are calculated in the current classifier space between the selected face/peripheral region(s) and the corresponding face/peripheral regions for all other images in the searched image collection. In the current implementation the Euclidean distance is used to calculate these distances which server as a measure of similarity between the selected face/peripheral regions.

(ii) The statistical mean and standard deviation of the distribution of these calculated distances is determined and stored temporarily.

(iii) The determined distances between each face/peripheral region and the selected face/peripheral regions are next normalized using the mean and standard deviation determined in step.

These normalized data sets may now be combined in a decision fusion process which generates a ranked output list of images. These may then be displayed in a UI module as described below.

An additional perspective on the above process steps is given in Fig 5. This illustrates three classifier spaces on the left-hand side and shows how a mean value and standard-deviation exists for each. Individual classifier values for a face region within a particular image can be normalized using these statistically derived quantities.

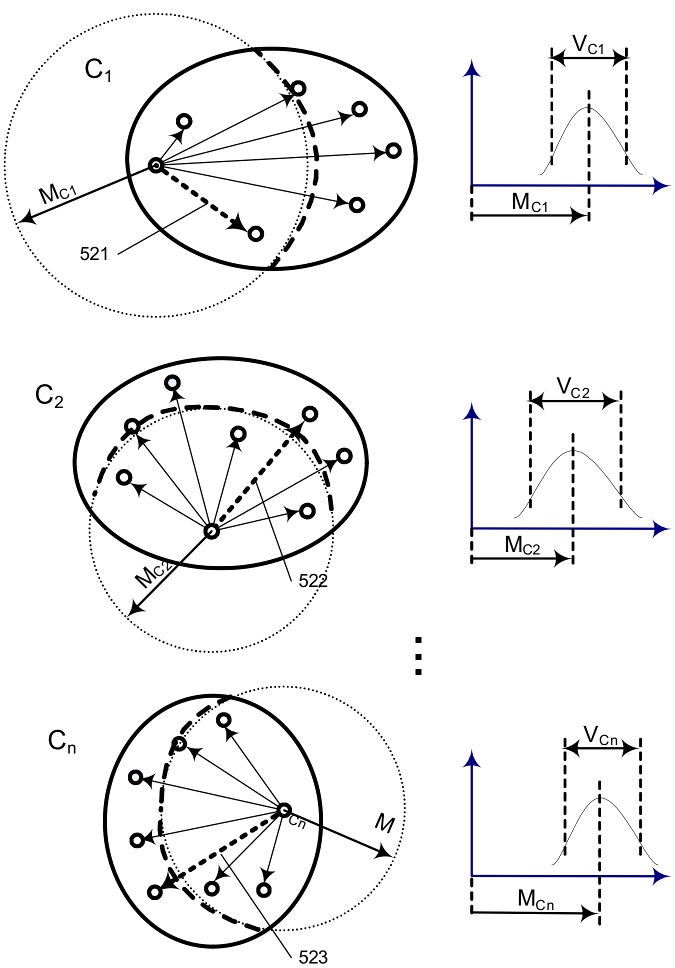

Fig 5: Combining Multiple Classifier Sets within an Image Collection using Statistical Normalization Techniques.

D. UI Module

This module handles *user interface* aspects of the system. It is designed to be suitable for in-camera applications.

Fig 6(a) illustrates the UI aspects of an application which employs the various software components of our system. A main image can be selected from a set of images which are accessed through a standard image browser and displayed as a set of thumbnail images. When a face region in this main image is clicked the application will automatically search through the other images in this collection and will sort and display these based on the image which contain face regions which are most similar to the selected face region.

If the use double-clicks, or selects an alternative option then the marked region in the main image expands to include the shoulders and hair of the person selected, and both face regions and the peripheral regions of hair and upper body are included in the set of classifiers used for sorting and ranking images within the collection.

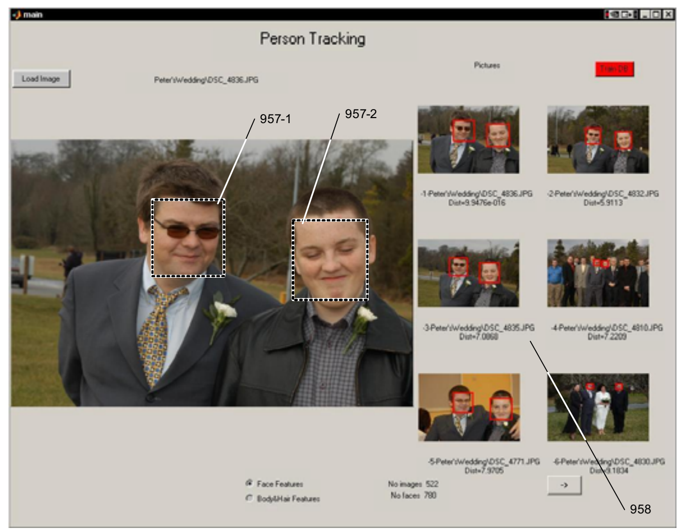

Fig 6(a): User Interface to the Image Sorting Application.

Fig 6(a) illustrates a further aspect of our system which allows a collection to be searched for a co-occurrence of two, or more, persons within an image. In this case two (or more) face regions are selected from an image and the image collection is searched for a co-occurrence of both faces.

This is achieved by only considering images in which there are at least two determined face regions. Similarity measures are then determined between each face region selected for retrieval purposes and the face regions in each image which has at least two face regions; this leads to two sets of classifiers, [C_{11}, C_{12} ...C_{1N}] and [$C_2$1, C_{22} ...C_{2N}]. A statistical distribution is associated with each classifier. These are now combined as illustrated in Fig 5(b) to yield a combined similarity measure (distance) between the selected pair of faces and each image in the collection. The closest images are then displayed in the UI.

E. Image Collection Data

Data from an image collection is written into a main dataset which includes (i) global data relating to the image collection; (ii) a list of image data records associated with the analyzed data obtained from each image. These image data records further contain data relating to the extracted face & peripheral regions detected in each image and the feature vector data extracted from from each region.

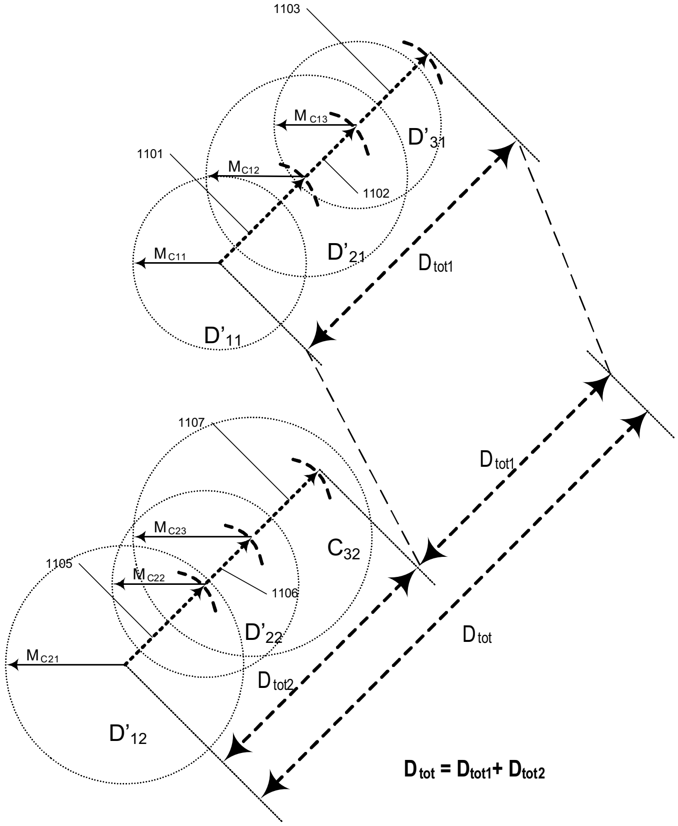

Fig 6(b): Combining Classifiers for two Face Region

IV. TECHNIQUES FOR COMBINING CLASSIFIERS

In this section we describe how classifiers may be normalized and how, in particular, heterogenous classifiers sets may be combined. Details are also given of how similarity measures may be determined for more than one reference pattern, thus allowing a selection of, and search for multiple face regions in an image.

A. Statistical Normalization Method

Fig 5 illustrates our primary technique for normalizing and combining the multiple classifiers described in this disclosure to reach a final similarity ranking. This process is a key aspect of the decision fusion process which will be described shortly.

The process is described for a set of multiple classifiers, C_1, C_2 ...C_N and is based on a statistical determination of the distribution of the distances of all patterns relevant to the current classifier from the selected retrieval pattern. For most classifiers this statistical analysis typically yields a normal distribution with a mean value M_{Cn} and a variance V_{Cn} as shown in Fig 5.

We remark that the determined statistical distribution is not necessarily a normal distribution, although practically all classifier distributions will be modeled as such. As an example, the distribution of the *correogram classifier* for the peripheral regions has a bimodal form. However this can be understood as occuring because it combines the distributions of both the hair and top-body regions; if these are separated and considered as two distinct classifiers then two separate normal distributions would result.

The combining of classifier similarity ranking measures (or, distances) is then determined by normalizing each classifier by this determined mean similarity ranking measure (distance) for that classifier, based on the selected retrieval pattern.

Thus the combined similarity ranking measure can now be determined quite simply as:

$$D_{combined} = D_1/M_{C1} + D_2/M_{C2} + ... + Dn/M_{Cn}$$

A more sophisticated determination may optionally incorporate the standard deviation of the statistical distribution into the normalization process. An improvement in algorithm performance by up to 10% from an 80-85% success rate, up to a 90—95% success rate in sorting/retrieval of images can be achieved by this simple technique of classifier normalization.

B. Similarity Measures for Heterogeneous Classifier Sets

So far we have been primarily concerned with cases where all classifiers are available for each test pattern. In the context of our working implementation this implies that both face recognition classifiers, top-body correlogram classifier and the hair region correlogram classifier are available. However this is not always the case. We can say that the face region classifiers should always be available once a face region is successfully detected. Hereafter we refer to such classifiers as primary classifiers. In contrast the hair and clothing classifiers are not always available for close-up shots or where a face regions is towards the periphery of an image. Hereafter we refer to such classifiers as secondary classifiers.

Thus when the decision fusion process performs a similarity determination across all stored patterns using all available classifiers some patterns may not have associated secondary classifiers. This may be dealt with in one of several ways

(i) patterns without an associated secondary classifier may have the missing similarity measure for that classifier replaced with the maximum measure determined for that classifier; or

(ii) such patterns may have said similarity measure replaced with the determined statistical mean measure for said classifier; or

(iii) such patterns may be simply ignored in the search.

In case (i) said patterns will appear after patterns which contain all classifiers; in (ii) the effect of the missing classifier does not affect the ranking of the pattern which may appear interspersed with patterns which contain all classifiers while in (iii) said patterns will not appear at all in the ranked list determined by the decision fusion process.

We remark that a selection between these alternatives may be based on pre-determined criteria, on a user selection, or on statistical analysis of the distribution of the classifier across the pattern set.

C. Determining Similarity Measures for Multiple Reference Patterns

A second modification of the decision fusion process arises when we wish to search for a combination of two, or more, reference patterns co-occurring within the same image. In this case we process the first reference pattern according to the previously described methods to obtain a first set of similarity measures. The second reference pattern is then processed to yield a second set of similarity measures. This process yields multiple sets of similarity measures.

We next cycle through each image and determine the closest pattern to the first reference pattern; if only one pattern exists within an image then that image will not normally be considered. For each image where at least two patterns are present we next determine the closest pattern to the second reference pattern. These two similarity measures are next combined as illustrated in Fig 6(b) where the normalized classifier similarity measures for reference pattern No.1, D'_{11}, D'_{21} and D'_{31} are combined with the normalized classifier similarity measures for reference pattern No. 2, D'_{12}, D'_{22} and D'_{32}. This provides a combined similarity measure, D_{tot}, for that pattern grouping within an image and is stored accordingly. After each image in the image collection is thusly analyzed a ranking list based on these combined similarity measures can be created and the relevant images sorted and displayed accordingly.

D. Employing User Input in the Combination Process

From the foregoing descriptions of the various methods of combining the normalized classifiers it is clear that, once the normalized classifiers for each pattern are determined, the main decision fusion process can combine these classifiers in a variety of ways and that the resulting images (pattern groupings) can be correspondingly sorted in a variety of ways with differing results.

Our application takes advantage of this by allowing a user to select/deselect different classifiers. In our current implementation we have found an optimum balance between computational complexity and accuracy of retrieval requires the use of 3 different face classifiers, 2 peripheral regions classifiers (hair and body) and a whole region classifier which encompasses the entire face and peripheral regions.

V. CONCLUSIONS

The system described in this paper has been implemented on a desktop computer. Initial testing indicates that accuracy rates of the order of 85-90% for correctly recognizing people are achieved without user intervention. These results are based on the use of a broad mix of images of varying qualities with image sets varying in size from 40-50 images up to a thousand images.

The sets of classifier data that needs to be associated with each face region, in order to achieve this level of accuracy, are of the order of several hundred bytes of data. Thus the data required for a large image collection of, say, 1000 images is somewhat less than 1MB. The search and retrieval process is also relatively fast once an image has been classified – typically it is less than 100 mS on a desktop PC for a collection size of the order of 300-400 images.

The principle bottleneck in our system is the face detection algorithm. This is based on a state-of-art algorithm [2] with certain enhancements to improve the detection speed. Nevertheless 85%-95% of the time required to classify a new image is spent on the face detection step. In practice this translates into several seconds per image on a desktop PC or somewhat longer on a state-of-art digital camera. Given that click-to-click requirements for modern cameras are somewhat less than 1 second it is evident that improved face detection methods would be required for a full in-camera implementation of the present system.

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