Tracking Human Object with Motion, Temperature and Heart Beat

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Abstract— Human Motion can be detected by measuring change in speed or vector of it in the field of view. Also the temperature and heartbeat of the human (target object) promotes more applications. The tracking architecture and dataset processing cannot perform the expected outcomes due to the limitations of data association (temperature and heart beat).A collaborative grouping of datasets is done using Gaussian Mixture Model (GMM). Hereby, the proposal discloses the motion tracking relationship among the different datasets using MC-IMME algorithm which is an improvement over the existing IMME algorithm. The efficient target estimation to employ a tracking relationship within a cluster is achieved using GMM and expectation-maximization algorithm.

Key words: Gaussian Mixture Model (GMM), Expectation-Maximization (EM), Interacting Multiple Model Estimator (IMME), Multichannel- IMME (MC-IMME)

I. INTRODUCTION

Image processing is any form of signal processing for which the input is an image, such as a photograph or video frame and the output of image processing may be either an image or a set of characteristics or parameters related to the image. Image processing techniques are 1) Image enhancement 2) Image restoration and 3) Image compression. The acquisition of images is referred to as imaging. The process of improving the quality of a digitally stored image by manipulating the image with software. Image restoration is used to exhibit the features of the image so that make the image is more pleasing to the observer.

Current to object detection are often categorised by top-down, bottom-up or combination of the two. Top-down approaches typically embody a coaching stage to get class-specific model options or to outline object configurations. Bottom-up approaches begin from low-level or mid-level image options, i.e. edges or segments . These ways build up hypotheses from such features, extend them by construction rules and so appraise by bound value functions. The third class of approaches combining top-down and bottom-up ways have become prevailing as a result of they cash in of each aspects. Though top-down approaches will quickly drive attention to promising hypotheses, they're susceptible to manufacture many false positives once options area unit domestically extracted and matched. Options among the same hypothesis might not be in step with relevancy low-level image segmentation. On the opposite hand, bottom-up approaches attempt to keep consistency in low level image segmentation, however typically would like rather more efforts in looking out and grouping.

Tracking human motion, body temperature and heart beat aids more application areas such as sports, health care, medical monitoring. By tracking more physical points (pixels)on the target object (human) more accurate information about target motion can be achieved. Heart beat is detected using QRS algorithm also the body temperature is detected using SST(Sea surface temperature) algorithm[14]-[15]. ECG provides the image of the electrical generation and reflects the excitation processing of the heart. Table 1. Lists the evolution of surveillance systems.

	Evolution	Characteristic	Systems
Surveillance Systems	First generation	Human supervision	CCTV
	Second generation	Automatic real time recognition	BEHAVE CAVIAR
	Third generation	Wide area surveillance	VSAM CBSR
	Fourth generation	Long term activity pattern statistics	IBM S3

Table 1: Past Surveillance Systems Based on Activity Recognition

II. EXISTING SYSTEM

The basic idea of all Multiple model(MM) approaches is that complicated target movements are made up of random variations originating from basic (straight-line) target motion. Due to the difficulty in representing this motion with a single model, MMs including potentially dynamic models operate in a parallel way with Markov switch probability. The main feature of the interacting multiple model (IMM) is the ability to estimate the state of a dynamic system with several behaviour models. IMME algorithm can be used to combine different filter models with improved control of filter divergence. As a suboptimal hybrid filter IMME makes the overall filter recursive by modifying the initial state vector and covariance of each filter through a probability weighted mixing of all the model states and probabilities.

This concept can estimate the object location as well as the velocity from measured datasets using multiple sensory channels we have extended the IMME to improve overall performance by adding switching probability to represent the conditional transition probability and a collaborative grouping method to select a proper group number based on the given dataset.The proposed method can achieve 50.94%improvement over IMME in the upper body motion.

The existing system has two limitations such as 1) it can only work with limited datasets and 2) it cannot guarantee the global optimal time sequential data due to the lack of adaptive parameter for the above sequence. The existing system uses MC-IMME,an improvement over IMME [1].

In MC-IMME, grouping data can be used for target-tracking estimation with IMME[1]. The interactive relationship can compensate for the prediction estimate error. An expectation–maximization (EM) algorithm isan iterative method for finding maximum likelihood or maximum a posteriori (MAP) estimates of parameters in statistical models, where the model depends on unobserved latent variables. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and maximization (M) step, computes parameters maximizing the expected log-likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step.

A. EM Algorithm:

1. Start with initial guesses for the parameters $\hat{\theta}^{(0)}$.
2. *Expectation Step*: at the jth step, compute
$$Q(\theta', \hat{\theta}^{(j)}) = \mathrm{E}\left(\ell_0(\theta'; \mathbf{t}) | \mathbf{z}, \hat{\theta}^{(j)}\right) \quad (4)$$
as a function of the dummy argument θ'.
3. *Maximization Step*: determine the new estimate $\hat{\theta}^{(j+1)}$ as the maximizer of $Q(\theta', \hat{\theta}^{(j)})$ over θ'.
4. Iterate steps 2 and 3 until convergence.

B. Disadvantages:

- AIC value is used to measure the relative quality of the model and it is used for model selection,which should be high but in this system it is minimum.
- There exists inconsistency in tracking the different physical points.

III. PROPOSED SYSTEM

In this paper we have proposed and designed Find- a real-time user tracking system which can perform device-free tracking of multiple (unknown and variable number of) users in the Hallway Environments with detection of their temperature and heart beat . The significance of our designed system are as follows: (a) fast tracking of individual targets (b) Scaling for multi-user tracking where user motion trajectories may crossover with each other in all possible ways.

- MC-IMME algorithm - filter models.
- Expectation maximization algorithm.
- QRS Algorithm- ECG applications.
- SST Algorithm- temperature tracking.

This system proposes 4 methods to segment the target(human)from the background such as moving region segmentation, morphological operations, human tracking and feature extraction which facilitates further processing. Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels).The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to understand . Each of the pixels in a region are similar with respect to some characteristics such as color , intensity, or texture. Fig 1. Illustrates the architecture of propsed system.

In moving region segmentation, the watershed transform is often applied to separate touching objects in an image . The watershed transform finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low.Segmentation using the watershed transform works better if you can identify, or "mark," foreground objects and background locations. The foreground and background markers are estimated. In morphological operations, a structuring element is applied to an input image, creating an output image of the same size. A structuring element is a matrix consisting of only 0's and 1's that can have any arbitrary shape and size. The pixels with values of 1 define the neighbourhood to the corresponding pixel.

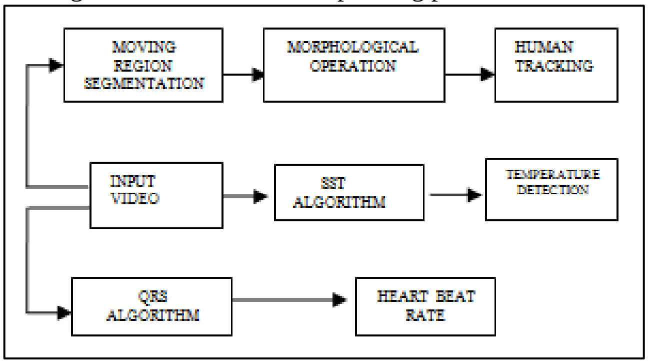

Fig. 1: Proposed System Architecture

Also the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors. By choosing the size and shape of the neighborhood, you can construct a morphological operation that is sensitive to specific shapes in the input image.The most basic morphological operations are dilation (adding pixels)and erosion(removing pixels).

The Pseudo code is

- Input: Given examples $\{x_i\}_{i=1}^{n}$ as well as the label for each example $o_i \in \{0,1,\ldots,C\}$, and the example $\dot{x}$, without label;
- Output: the label o of the example x^*;
- Algorithm:

--Split the training data into c subsets according to the labels;

--For each subset of a certain class c,

Do:

--Initialize: $\theta_c = \{w_i, \mu_i, \Sigma_i, i = 1, 2, \ldots, k\}$;

--Repeat until convergence:

--Expectation: compute the expectations $E(z_i^j | x_i, \theta_c)$ using (12);

--Maximization: update the parameters $\theta_c <- argmax(L(\theta, \theta_c))$ using (14);

--Store the parameters $\theta_c^{\#}$;

--Compute the expectation of $E(z_*^j)$ for x^*, and then calculate the likelihood using (13) for each class;

--Find out $\bar{c} = argmax(L(x, \theta_c))$;

--Output $\bar{c}$ as the label of x^*;

- End.

The next is human tracking where scaling(resizing) technique is employed such that the target changes its distance to the camera lens. That leads to a change in size of its appearance in the image.Shadows change the color distribution and may weaken the contrast of the target's edges. Occlusion is a problem in tracking indeed. The task of the tracker is to recover the temporarily occluded target. There are two aspects of occlusion. A target may be occluded by an object in the scene which has no relation to the tracking process. Then again, if we were to track multiple objects, the objects could be occluding one another. Distinct facial expressions can become a problem because they change the texture of the face.

The last module of tracking human motion is feature extraction which is a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval.Feature detection, feature extraction, and matching are often combined to solve common computer vision problems such as object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification.

Advantages:

- Object Location And Velocity.
- Data Association -Gmm.
- Improvement Over Imme

IV. EXPERIMENTAL RESULTS

An electrocardiogram (ECG), is a graphic tracing of the voltage generated by the cardiac or heart muscle during a heartbeat. It provides very accurate evaluation of the performance of the heart. The heart generates an electrochemical impulse that spreads out in the heart in such a fashion as to cause the cells to contract and relax in a timely order and, thus, give the heart a pumping characteristic

QRS detection algorithm is used for ECG applications. Electrocardiogram (ECG) records excitation processes of heart in the form of waves, peaks and lines which depicts in Fig 2.

Fig. 2: ECG Diagram

An ECG has five deflections, which is shown in Fig 3. arbitrarily named "P" to "T" waves. The Q, R, and S waves occur in rapid succession, do not all appear in all leads, and reflect a single event, and thus are usually considered together. A Q wave is any downward deflection after the P wave. An R wave follows as an upward deflection, and the S wave is any downward deflection after the R wave. The T wave follows the S wave, and in some cases an additional U wave follows the T wave.

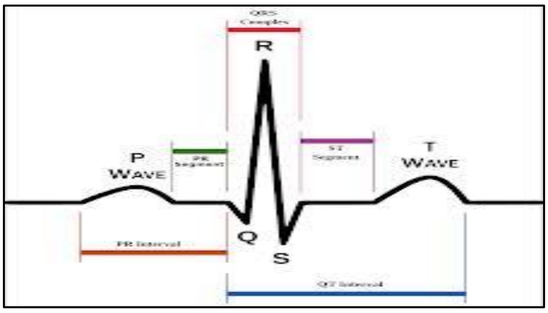

Fig. 3: QRS Diagram

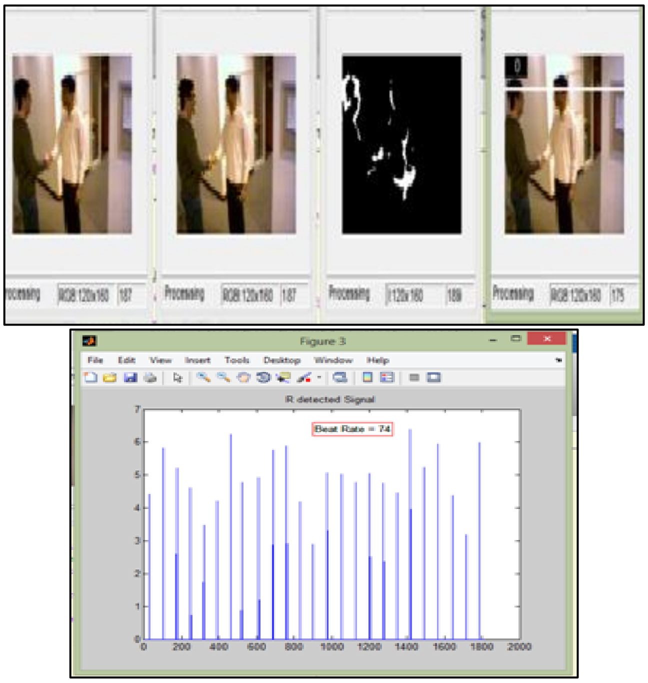

Fig. 4: Outline The Object Detection Process And The Record Of Heart Beat Rate Of The Examinee.

Normal human body temperature, depends upon the place in the body at which the measurement is made, and the time of day and level of activity of the person. Sea Surface Temperature (SST) algorithm is used for tracking the body temperature of target (human). Sea Surface Temperature (SST)is a significant parameter, in the ocean environment. SST refers to the temperature of the ocean skin using remote sensing technology.

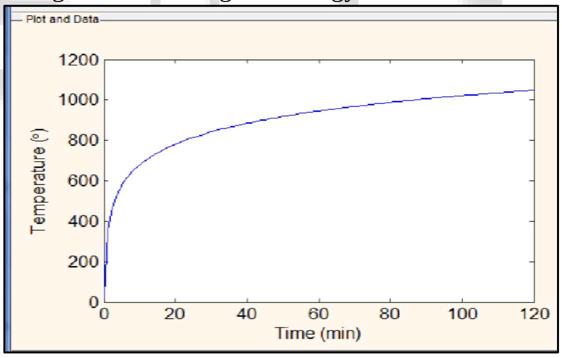

Fig. 5: Different Temperatures Recorded At Different Time Intervals According To The Activity Of The Target.

V. CONCLUSION

Human Motion can be detected by measuring change in speed, the temperature and heartbeat of the human (target object) . The tracking architecture and processing is explained and the results outcomes will solve the limitations of data association (temperature and heart beat) .A collaborative grouping of datasets is done using Gaussian Mixture Model (GMM). Hereby, the proposal disclosed the motion tracking relationship among the different datasets using MC-IMME algorithm which is an improvement over the existing IMME algorithm. As discussed earlier the input is a video which is processed to get the desired output. Here the motion of the target is tracked based on the input video of specific format and specification which can be extended in future to directly give the video from the camera.

VI. FUTURE ENHANCEMENT

This work can be extended in future to directly give the video from the camera and in any format for futher processing. Physical sensors can be used in the project to process real time videos and the heart beat and body temperature computation can be correlated to get desired output.

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