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Outline Track Algorithm Based on ICA Shape Feature

Zeng Rui and Wang Ying-yan
School of Electro-mechanical and Information Technology, Yi Wu Industrial and Commercial College, Yi Wu, China

Abstract: We design is based on the shape of the outline track ICA energy model and derive the evolution curve gradient flow equations. The first part of the energy functional is based on a priori information about the shape of the energy term, used to constrain the active outline. Active Outline and expectations in the evolution of the shape of constantly comparing it with apriori shape model to match. The second part is the image energy term, the candidate target area by minimizing the covariance with the template from the background region candidate while maximizing the covariance with the template from the evolution of the evolution of the curve to the target location. The third part is the length of the term, limiting the evolution of the curve and make a smooth curve. Validated based on ICA shape outline track algorithm is effective, we have a different image sequence of human walking on the test. Experimental results show that our proposed algorithm processing including noise, illumination variation and complexity of issues such as the background image is robust.

Key words: ICA, outline track, gradient flow equations, image energy term

INTRODUCTION

Computer vision (also known as machine vision or image analysis and understanding) is a study of visual function using computer simulations of biological science, the ultimate goal is to the computer instead of the human eye and brain to realize the perception of the surrounding environment as well as a deeper understanding (Hosseini and Deville, 2004). Moving target segmentation and tracking technology is the core of computer vision system is a fusion of a number of areas (such as image processing, pattern recognition, applied mathematics, physics, etc.) research project, has now become the image and video applications important part.

Based on the video frequency movement target tracking is one of computer vision domain main research directions. It in intelligent transportation supervising and managing, man-machine interaction, the computer animation, the visual navigation, the medicine diagnosis and so on the multitudinous domains all has the widespread application. Since (Hu *et al*., 2005) in the outline track domain groundbreaking work, the outline track has always been tracks the domain the research hot spot. Not only the initiative outline model considered also may unify the goal by the image data restraint the shape as well as the position and so on the prior restraint. Unifies in the geometry initiative outline model the apriori information to be possible to solve questions to a certain extent and so on goal apparent change, illumination change, mask, noise, then enhancement track algorithm robustness. In addition, the initiative outline model also supports and the human in the later period interactive.

INDEPENDENT COMPONENT ANALYSIS

Independent component analysis (ICA) is the 1990s development of a new signal processing technology, it is rooted in blind source Signal Separation problems (BBS) solution (Ku *et al*., 1995). Blind source Signal Separation problems is the only advantage of multiple output from the sensor (Lee *et al*., 2004). Observation of the mixed-signal) to separate and extract the source signal and the "blind" has two meanings: (1) Source signal is not observed (2) Mixed system parameters is unknown. The scientific research and engineering applications, we can assume that observation signal is generated by an invisible source signal of a mixture. Here is a simple and typical example is that the "Cocktail Party" problem. In the cocktail on the different place a group microphone, when a lot of people (as a different sound source) at the same time in one room, this group microphone has recorded the sound signal, each microphone records the signals are all sound of mixed (Correa *et al*., 2005). BBS subject of study is how to only from the group observing signal extraction in each individual sound signal (Lu *et al*., 2008). ICA technology is also addressed in blind source Signal Separation problems, continue to enrich and develop and it is from the multi-dimensional statistical data to find

Corresponding Author: Zeng Rui, School of Electro-mechanical and Information Technology, Yi Wu Industrial and Commercial College, Yi Wu, China

implied factor or a separate component of the method. The linear transformation and linear space perspective, the source signal is independent of the non-Gaussian signal, can be seen as a linear space of the signal, an observation signal is the source signal (the signal) of the linear combination, the Independent Component Analysis (ICA) is the source signal and the linear transformation is unknown, from the observed mixed-signal in the data space of the base, the source signal (Montgomery, 2005).

The current ICA research is focused on the basic theory and algorithms. The study will include information theory-based (Information entropy and mutual information, entropy and so forth) of the iterative estimation methods and based on statistics (high-level, high-level cumulative amount of algebraic methods two categories, in essence, they are using the source signal of the non-Gaussian and independence the two features. Researchers have already made a lot of good estimate algorithm, such as FastICA algorithm (Nomikos and MacGregor, 1995), Infomax algorithm (Shao *et al.*, 1999), maximum-likelihood estimated algorithm (Sun and Tsung, 2003), stage 2 Cumulative Quantity, 4 bands cumulative quantity and so on and each algorithm has its pros and cons. The ICA had been widely applied to image processing, face recognition, feature extraction, biomedical signal processing, speech signal processing, communication systems and finance and has achieved good results (Petersen *et al.*, 2000). These applications demonstrate the ICA of features and value.

ICA linear model: ICA model consists of a linear mixed model and separation model of two parts, shown in Fig. 1.

First, focus on ICA's linear mixed models, $X = [x_1, x_2, \ldots, x_n]^T$ is n-dimensional observation signal, It is linear composed of m unknown independent source signal $S = [s_1, s_2, \ldots, s_n]^T$ and n * m of the unknown matrix $H = [h_1, h_2, \ldots, h_n]^T$:

$$x = Hs = \sum_{i=1}^{m} h_i s_i, i = 1, 2, \cdots, m \quad (1)$$

Expand the formula to be:

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} h_{11} & \cdots & h_{1m} \\ \vdots & \vdots & \vdots \\ h_{n1} & \cdots & h_{nm} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{bmatrix} \quad (2)$$

by the above equation, after in the hybrid matrix A each course quantity m element took separately m source vector the weighting factor carries on the mix to be possible to obtain a corresponding observation signal.

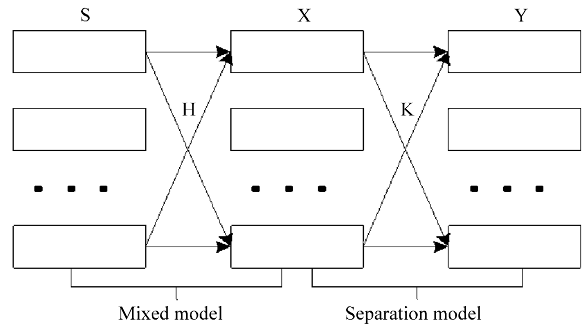

Fig. 1: ICA linear model

By a known observation of the signal x in a mixed matrix H unknown circumstances the unknown source signal S is a ICA model. ICA method of the basic goal is to find a linear transformation the separation matrix K, so that:

$$y = Kx = KHs \quad (3)$$

Can approximate the real source signal S Output Y is the source signal S an estimate. When the split matrix K, real source signal to be separated, otherwise the separation of the magnitude of the signal and sort order with the source signal differences in ICA is the uncertainty.

The P = KH, P Performance Matrix, can be used to measure ICA algorithm the separation performance.

In the above ICA model, has following supposition condition:

- Source signal s various components statistical independence, namely must satisfy:

$$p(s) = \prod_{i=1}^{m} p(s_i)$$

- Observation signal number is bigger than is equal to the independent component (source signal) the number
- Hybrid matrix H is the row non-singular matrix
- Source signal are most only then a Gauss signal

The following questions in order to simplify the cocktail party give a specific example.

Figure 2, it is assumed there are two sound sources s1, s2, the room there are two microphones x1, x2 recorded

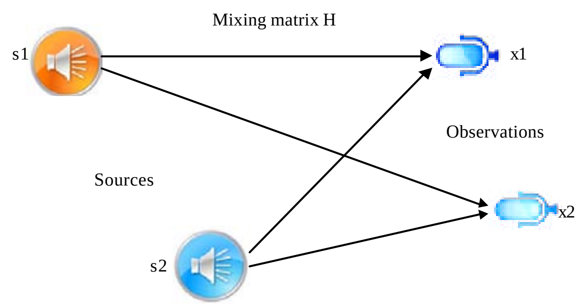

Fig. 2: cocktail party question example

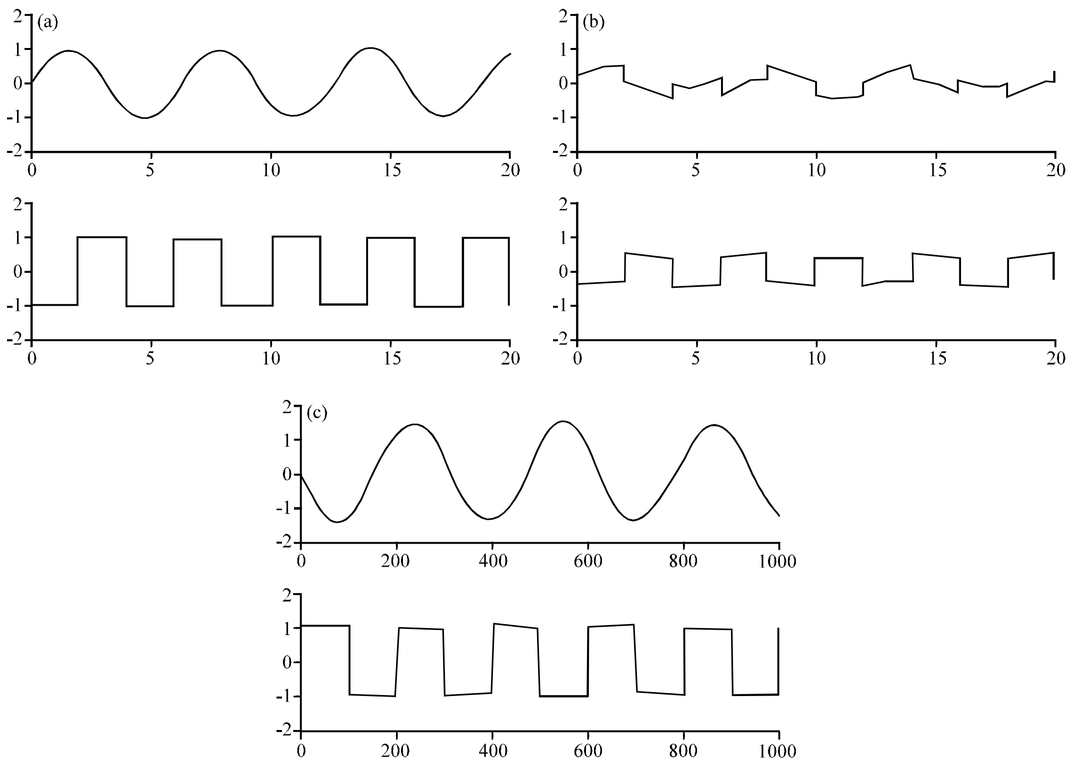

Fig. 3(a-c): Signal mixing and separation, (a) Two Independent source signals s1, s2, (b) Mixed signal x1, x2 and (c) ICA separation of the independent signal

the sound signal. Each microphone records the sound source signals are mixed two. Assuming mixing matrix is H, then x = HS:

$$x_1 = h_{11}s_1+h_{12}s_2$$

$$x_2 = h_{21}s_1+h_{22}s_2$$

As shown in Fig. 3, two independent source signals s1, s2, the mixed signal x1, x2 and separated by means ICA independent signals.

Outline track algorithm based on ICA shape feature: First, design contour tracking energy model based on ICA shape modeling and infer the evolution curve gradient flow equations. Final walk through multiple sets of body image sequence verified the validity of the proposed algorithm.

First of all, design is based on ICA shape track modeling the outline track energy model and derive the evolution curve of the gradient flow equation. The multi-group human walking image sequence of the proposed algorithm The validity has been verified.

Energy model based on prior information: The model used in the level set function under the premise, we match the outline model based on covariance, prior shape and length constraints into an energy model, this model combines three advantages. Energy functional using three linear combination, the expression is as follows:

$$E = \lambda_1 E_{sahpe}(\phi, A, \omega) + \lambda_2 E_{image}(\phi) + \lambda_1 E_{length}(\phi) \quad (4)$$

Among:

$$E_{shape}(\phi, A, \omega) = \int_\Omega \delta_\alpha(\phi)(s\phi - \phi_P(A))^2 \, d\Omega \quad \text{where } \alpha >> \varepsilon$$

$$\begin{aligned} &E_{sahpe}(\phi) = \gamma\|InS_R - InS_T\|_F - \eta\|InS_{R^c} - InS_T\|F \\ &E_{1ength}(\phi) = \int_\Omega \Delta H(\phi)| \, d\Omega \end{aligned} \quad (5)$$

where, λ_1, λ_2, λ_3, respectively is the energy functional three weight coefficient. The energy functional first part is based on the apriori information shape energy term, uses for to restrain the active outline. The initiative outline carries on the unceasing comparison in the evolutionary process neutral expectation shape, causes it to match with the prior shape model, to processes contains question and so on mask, noise, illumination change and complex background images has robustness (Hu *et al*., 2005). The second part is the image energy term, uses based on the covariance match initiative outline model, is away from simultaneously the maximization candidate background region and the template covariance distance through the minimizing candidate target sector and the template covariance causes in the evolution the curve to the target location evolution. The third part is the length item, through minimum about length of curve energy functional, the limit curve evolution and causes the curve to be smooth.

Prior shape item: There are many ways of putting priori into active outline model. Affected by the proposed methods such as M.Rousson, N. Paragios, a priori shape with a minimum of privacy, the outline and similarity of the transformation of the a priori of the square and (SSD) to define it.

Assumptions for two-dimensional rigid transformations:

$$A(x, y) = sR_\theta \begin{pmatrix} x \\ y \end{pmatrix} + T \quad (6)$$

Among:

$$R_\theta = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}, \; T = \begin{pmatrix} T_x \\ T_y \end{pmatrix} \quad (7)$$

This rigid transformation consists of four parameters, s expressed the reproduce by pantograph parameter, θ expression degrees rotation, (T_x, T_y) expresses the translation vector. Assuming that symbol the distance function $\phi_P(x, y)$ is by $\phi(x, y)$ after the rigid transformation is similar, then they should be met:

$$\begin{cases} x, y \rightarrow A(x, y) \\ \phi(x, y) \approx \phi_P(A(x, y)) \end{cases} \quad (8)$$

Therefore, the region near the curve data more meaningful, then prior shape item defined as:

$$E_{shape}(\phi, A, \omega) = \int_\Omega \delta_\alpha(\phi)(s\phi - \phi_P(A))^2 \, d\Omega \quad (9)$$

Among, ϕ is the target contour level set function, $\delta_\alpha()$ is the Dirac function and $\alpha > \varepsilon$, s represents scaling parameters, ϕ_P is a priori shape. Considering these prior information, the best conversion should be said that the current target level set is mapped to the training set in the shape of a class. If a shape representation ϕ_P belong to this category, then it by the average shape and separate components:

$$\phi_P = \overline{\Phi} + \sum_{i=1}^{m} \omega_j s_j \quad (10)$$

After the introduction of the weight vector $\omega = (\omega_1, \omega_2, \ldots \omega_m)$ shape energy term function is:

$$E_{shape}(\phi, A, \omega) = \int_\Omega \delta_\alpha(\phi)\left(s\phi - \left(\overline{\Phi}(A) + \sum_{i=1}^{m} \omega_j s_j(A)\right)\right)^2 d\Omega \quad (11)$$

In order to minimize the evolution of the curve and global similarity transformation of the energy functional, we use the gradient descent method, the evolution of the level set and gradient descent flow of the parameters as follows:

$$\begin{aligned} &\frac{d\phi_{shape}}{dt} = -2\delta_\alpha(\phi)s(s\phi - \phi_P(A)) - \frac{d\delta_\alpha(\phi)}{d\phi}(s\phi - \phi_P(A))^2 \\ &\frac{ds}{dt} = 2\int_\Omega \delta_\alpha(\phi)(s\phi - \phi_P(A))\left(-\phi + \nabla\phi P(A).\frac{\partial A}{\partial s}\right) d\Omega \\ &\frac{da_i}{dt} = 2\int_\Omega \delta_\alpha(\phi)(s\phi - \phi_P(A))\left(-\phi + \nabla\phi P(A).\frac{\partial A}{\partial s}\right) d\Omega \quad \text{with } a_i \in \{\theta, T_x, T_y\} \\ &\frac{\partial A}{\partial s} = R_\theta \begin{pmatrix} x \\ y \end{pmatrix}, \; \frac{\partial A}{\partial \theta} = s\partial_\theta R_\theta \begin{pmatrix} x \\ y \end{pmatrix}, \; \frac{\partial A}{\partial T_s} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \; \frac{\partial A}{\partial T_y} = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \end{aligned} \quad (12)$$

For solving the weight vector $\omega = (\omega_1, \omega_2, \ldots \omega_m)$, we give the optimal parameters of the closed-form solution, namely solving linear system $\bar{s}\omega = b$, among:

$$\begin{cases} \overline{S}(i, j) = \int_\Omega \delta_a(\phi)\left(s\phi - \overline{\Phi}(A)\right)S_i\ (A)\ d\Omega \\ b\ (i) = \int_\Omega \delta_a(\phi)\left(s\phi - \overline{\Phi}(A)\right)S_i\ (A)\ d\Omega \end{cases} \quad (13)$$

where, $\overline{s}$ is a m*m positive definite matrix. Here on the closed-form solution for proof:

$$E_{shape}(\phi, A, \omega) = \int_\Omega \delta_a(\phi)\left(s\phi - \left(\overline{\Phi}(A) + \sum_{i=1}^{m} \omega_j s_j\ (A)\right)\right)^2$$

Minimize:

Let the weight vector of extreme points satisfy:

$$\frac{\partial E_{shape}}{\partial \omega_2} = 0$$

where, i = 0, 1, ..., m, so:

$$\int_\Omega \delta_a(\phi)\left(s\phi - \left(\overline{\Phi}(A) + \sum_{i=1}^{m} \omega_j s_j\ (A)\right)\right).2.(-1).S_i(A)d\Omega = 0 \quad (14)$$

After simplification:

$$\Rightarrow \int_\Omega \delta_a(\phi)\left(s\phi - \overline{\Phi}(A)\right)s_i(A)d\Omega = \int_\Omega \delta_a(\theta)\sum_{i=1}^{m} \omega_j s_j\ (A)S_i(A)d\Omega$$

$$\Rightarrow \int_\Omega \delta_a(\phi)\left(\left(s\phi - \overline{\Phi}(A)\right)s_i(A) - \sum_{i=1}^{m} \omega_j s_j\ (A)S_i(A)\right)d\Omega = 0$$

$$= \sum_{i=1}^{m}\left(\omega_i \int_\Omega \delta_a(\phi)S_i(A)S_i(A)s\Omega\right)$$

For i to satisfy:

$$\int_\Omega \delta_a(\phi)\left(s\phi - \overline{\Phi}(A)\right)s_i(A)d\Omega = \sum_{i=1}^{m}\left(\omega_i \int_\Omega \delta_a(\phi)S_i(A)S_i(A)s\Omega\right)$$

This constraint constitutes the above linear system.

Image energy item: There are many outline track method based on partial differential equation, we use Ma Bo etc propose initiative outline model based on the covariance match. Based on in the covariance match track model image energy term definition is:

$$E_{image}\ (\phi) = \gamma \|InS_R - InS_T\|_F - \eta \|InS_R{}^c - InS_T\|_F \quad (15)$$

Among them, $\|_F$ represents the Frobenius matrix norm, S_T is the template covariance matrix. For a given image plane Ω, $\Omega \subset R^2$, f (x, y) is the corresponding pixel of the image feature vectors extracted. Assumed that the image plane is the closed contour curve Z (s) is divided into two parts, s is the arc length parameter, R is the area inside of the curve in mind, R^c is the outer region, $S_R{}^C$ and $\Omega \subset R \cup R^C$, S_R, respectively are region R and the R_C covariance matrix, the expression are:

$$S_R(\phi) = \frac{\int_\Omega H(\phi)(f(x,\ y) - \mu_R(\phi)(f(x,\ y) - \mu_R(\phi))^T dxdy}{\int_\Omega H(\phi)dxdy} \quad (16)$$

$$S_{R^c}(\phi) = \frac{\int_\Omega (1 - H(\phi)(f(x,\ y) - \mu_{R^c}(\phi)(f(x,\ y) - \mu_{R^c}(\phi))^T dxdy}{\int_\Omega H(\phi)dxdy} \quad (17)$$

Among:

$$\mu_R(\phi) \frac{\int_\Omega H(\phi)(f(x,\ y)dxdy}{\int_\Omega H(\phi)\ dxdy}$$

Represent the average value vector in candidate target sector R:

$$\mu_{R^c}(\phi) \frac{\int_\Omega H(\phi)(f(x,\ y)dxdy}{\int_\Omega H(\phi)\ dxdy}$$

Represent the average value vector of candidate background region R^c. H (ϕ) is Heaviside function, defines as follows:

$$H(\phi) = \begin{cases} 1 & \text{if } \phi \geq 0 \\ 0 & \text{else} \end{cases} \quad (18)$$

where, γ and η control prospect information and background information of the weight. Very little of the energy of the letter means that very little of candidate target regions with a template of the Association's distance from the great, candidate Background and objectives of the association between parties. In some cases, the image energy only needs to take into account future prospects and the template of the Association's distance from you can achieve better tracking results, in this case, it is desirable $\eta = 0$. However, when the target of the local covariance matrix and the covariance matrix is similar to the type of image energy, it is likely that evolution of the contour converged to the target part, to extract the accurate shape, in this case, the image energy in great, prospects and template-similarity, it is also necessary to take into account background and template between the similarities.

Image energy of lower gradient stream is:

$$\frac{\partial\phi_{image}}{\partial t} = -\frac{\partial E_{image}}{\partial\phi}$$
$$= \frac{-\lambda}{\|\Theta_1\|_F}\sum_{i=1}^{d}\sum_{j=1}^{d}(\Theta_1)_{i,j}\left(S_R^{-1}\ (\phi)\ \frac{\partial S_R(\phi)}{\partial\phi}\right)_{i,j}$$
$$+\frac{-\eta}{\|\Theta_2\|_F}\sum_{i=1}^{d}\sum_{j=1}^{d}(\Theta_2)_{i,j}\left(S_R^{-1}\ (\phi)\ \frac{\partial S_R(\phi)}{\partial\phi}\right)_{i,j} \quad (19)$$

Among:

$$\begin{cases} \Theta_1 = \text{In}S_R - \text{In}S_{r'},\ \Theta_2 = \text{In}S_{R^c} - \text{In}S_T \\ \frac{\partial S_R}{\partial\phi} = \frac{\delta(\phi)}{A_R}\left(ff^T - \frac{1}{A_R}\int_\Omega H(\phi)ff^T d\Omega - f\mu_R^T - \mu_R f^T + 2\mu_R\mu_R^T\right) \\ \frac{\partial S_{R^c}(\phi)}{\partial\phi} = \frac{\delta(\phi)}{A_{R^c}}\left(-ff^T + \frac{1}{A_{R^c}}\int_\Omega H(-\phi)ff^T d\Omega + f\mu_{R^c}^T - \mu_{R^c}f^T - 2\mu_{R^c}\mu_{R^c}^T\right) \\ A_R = \int_\Omega H(\phi)d\Omega,\ \ A_{R^c} = \int_\Omega H(-\phi)d\Omega \end{cases} \quad (20)$$

Because our energy functional is based on the variation frame, therefore we may use other track model to carry on the model conveniently to the image energy term.

Length item: Length is set to make the curve smoother, expression is:

$$W_{length}(\phi) = \int_\Omega |\nabla H(\phi)|\, d\Omega = \int_\Omega \delta\ (\phi)\,|\nabla\phi|\, d\Omega \quad (21)$$

Is the Dirac function, using the variation method, gradient downflow can be obtained:

$$\frac{d\phi_{length}}{dt}\ \ \delta(\phi)\text{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right) \quad (22)$$

where, div () is seeking scatter symbols can be evaluated by finite-difference.

Gradient downflow and track algorithm: Integrated each energy item the gradient downflow to be possible to obtain the total energy functional gradient downflow is:

$$\begin{cases} \frac{d\phi}{dt} = \lambda_1.\frac{d\phi_{shape}}{dt} + \lambda_2.\frac{d\phi_{image}}{dt} + \lambda_3\frac{d\phi_{length}}{dt} \\ \frac{ds}{dt} = 2\int_\Omega \delta_a(\phi)\left(s\phi - \phi_P(A)\right)\left(-\phi + \nabla\phi P(A).\frac{\partial A}{\partial s}\right)d\Omega \\ \frac{ds}{dt} = 2\int_\Omega \delta_a(\phi)\left(s\phi - \phi_P(A)\right)\left(\nabla\phi_P(A).\frac{\partial A}{\partial a_i}\right)d\Omega \quad \text{with } a_i \in \{\theta,\ T_x,\ T_y\} \end{cases} \quad (23)$$

Regard solution of the weight vector $\omega = (\omega_1, \omega_2, \ldots \omega_m)$, we through solution linear system $\bar{s}\omega = b$, obtain the most superior parameter seal solution. By combining independent component analysis of a priori information of the covariance matching tracking algorithm as follows:

- For tracking the first frame of the sequence, surrounded by manually initialize the target curve, established for the target area as a template for the covariance matrix of the covariance matrix
- There could be errors due to manually select, for some image sequences, using the traditional geometric active contour model (C-V model) to split the object outline, outline makes getting closer to the real goals. (Optional)
- According to the original objectives of the position and the training set shape average value position calculating the initial similarity transformation parameters s, θ, T_x, T_y, the parameter solution obtains through the Procrustes analytic method
- Get a new frame of the image, the frame based on the results, according to the energy and the gradient downflow formula to be iterative, update level set function and similarity transformation parameters, s, θ, T_x, T_y in each iteration, by the linear system update weight vector $\omega = (\omega_1, \omega_2, \ldots \omega_m)$
- Judgment iterates whether terminated, here uses iterative termination criterion for following two points
  - Calculate the current zero level set inside the covariance matrix from the template covariance matrix and the distance to determine if distance is less than the stated value, the iteration terminates, or vice versa to continue iteration
  - Judgment if iterative process has reached a predetermined number of iterations, the iteration terminates, or vice versa to continue iteration Eq. 6 Go to Eq. 4

The level set in the evolution, use the quick algorithm, such as narrow-band algorithm, only calculate curve near the narrow-band, thereby reducing computation.

Experimental results and analysis: In its pilot phase, use:

$$f = [r,\ g,\ b,\ I_x,\ I_y,\ I_{xx},\ I_{yy},\ I_{xy},\ \sqrt{I_x^2 + I_y^2}\,]^T$$

As each pixel of the feature vector. In order to make the energy functional to achieve global minimum, use the normalized function $H_\epsilon(\phi)$, $\delta_\epsilon(\phi)$ instead of $H(\phi)$, $\delta(\phi)$:

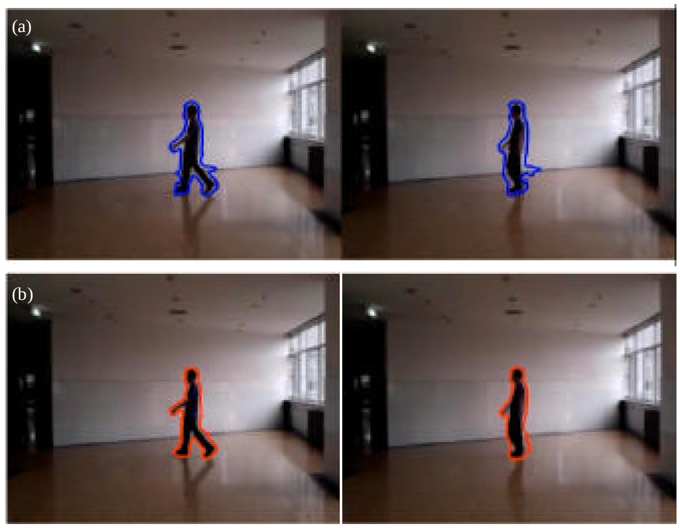

Fig 4(a-b): (a) Sequence 1 of track result (CMPCT) and (b) Sequence 1 of track result (Our method)

$$H_\varepsilon(\phi) = \frac{1}{2}(1 + \frac{2}{\pi}\arctan(\frac{\phi}{\varepsilon})),\ \delta_\varepsilon(\phi) = \frac{1}{\pi}.\frac{\varepsilon}{\varepsilon^2 + \phi^2}$$

The effective area of δ_ε (ϕ) can choose different ε adjustments, when ε>0, H_ε (ϕ)→H (ϕ) and δ_ε (ϕ)→δ (ϕ). In the experiment, we establish ε = 2.Pays attention to in formula (3.20) δ_α (ϕ) α to correspond ε, in the experiment takes α = 60.

Because of our algorithm is a priori information and image energy combination. Therefore, in the experiment, we will work with the covariance matching the Outline Track algorithm to track the results. For the sake of convenience, we will be based on covariance matching the outline-following algorithm abbreviated as CMPCT. In the CMPCT algorithm shape item the algorithm which proposed with us differs from, its formula is as follows:

$$E_{shape}(\phi) = \int_\Omega H(\phi) - H(\bar{\phi}(a.r.x + T)))^2\,dx \qquad (24)$$

where, α, r, T are the scale, rotation and translation parameters. It is different from our similar parameter as well as the goal outline iterate, CMPCT algorithm assumes α, r, T known before iteration of the frame. For each of the frame image, CMPCT algorithm of similar transformation parameters selection principle is causes to have $\phi(\alpha.r.x{+}t)$ the track result which obtains with on one to be closest. $\phi(x)$. Is a level set function, the zero level set is the destination profile templates, typically by the first frame to manually label the target outline.

Carries on the appraisal to the track effect the strategy to have very many, according to the outline track characteristic, this article uses overlaps rate this target to carry on the appraisal to the algorithm track effect. Overlaps rate is tracks the result to surround the region and the goal real outline surrounds the region the overlap region and the merge region area ratio. The formula is as follows:

$$\text{Ratio} = \frac{AREA_{real} \bigcap AREA_{exp}}{AREA_{real} \bigcup AREA_{exp}} \qquad (25)$$

$AREA_{real}$ represents the inside area of the target real outline, $AREA_{exp}$ represents the inside area of the experimental tracking results outline. When the real object result outline and experimental result objectives outline completely overlap, overlap rate of 1, the result is lost when the tracking target overlap was 0. Overlap rate is higher, tracking the better.

We demonstrate through several sets of experiments presented in this paper with the new prior shape tracking algorithm. These experiments video mainly for the following two aspects: Walking side, complex background.

Experiment a: As Fig. 4a by shows, experiment select people in indoor walking of image sequence as test object, each frame are for track, total track frame number for 90 frame, take people of overall as track of target, the sequence of features is target deformation larger, walking in the people in ground Shang of shadow and wall surface and ground junction of that article is obvious of line and target table view compared similar, this makes shape of precise extraction more difficult. Fig. 4a and b, respectively CMPCT algorithm and algorithm of our xperimental results. From Fig. 4a it can be seen that CMPCT track results under the influence of wall and floor junctions, poor results, body contour extends to the two sides of the error. Because of the combination of shape based on independent component analysis constraint, our algorithms to get good side profile curve of the human body track results.

SUMMARY

We have conducted the thorough research to in the level collection method shape prior study question. Introduced in the visual track introduces the apriori information the reason. The shape apriori information which obtains with based on the covariance match track unifies and infers the corresponding gradient class using the calculus of variations. The concrete innovation is as follows:

- Using the level set method for shape representation, this method has the following features. First, the shape of the expression method is implicit, intrinsic, avoiding the cumbersome manual to determine markers and error and easy to extend to higher dimensional case. Second, the level set independently of the contour parameterization, the topology with adaptive capabilities. Finally, the level set method and the expression of the shape of the curve based on level set evolution variation model is consistent, it can be easily integrated into a variety of active contour model. Subsequently, we have to set the level of implicit representation of the training set shape independent component analysis, the source shape and the establishment of an independent component analysis based on the statistical shape model
- We designed a model based on the shape of the contour tracing ICA energy model and derive the evolution curve gradient flow equations. The first part of the energy functional is based on a priori information about the shape of the energy term, used to constrain the active outline. Active Contour and expectations in the evolution of the shape of constantly comparing it with prior shape model to match. The second part is the image energy term, the candidate target area by minimizing the covariance with the template from the background region candidate while maximizing the covariance with the template from the evolution of the evolution of the curve to the target location (Nomikos and MacGregor, 1995). The third part is the length of the term, limiting the evolution of the curve and make a smooth curve

In order to verify the proposed model based on the active outline shape ICA tracking effectiveness of the algorithm, we are in a different image sequence of human walking on the test. Experimental results show that our proposed algorithm for dealing with complex issues such as the background image is robust.

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