On motion periodicity of dynamic textures

Dmitry Chetverikov and Sándor Fazekas
Computer and Automation Research Institute
Budapest, Hungary
csetverikov@sztaki.hu

Abstract

Dynamic textures (DTs) are videos of natural or artificial processes, such as waves, smoke, fire, or walking crowd. While activities and motion events produced by moving shapes are well localised in space and time, the spatiotemporal extent of most natural DTs is less definite. The notion of periodicity, or regularity, has been extensively studied in static texture analysis and in activity analysis, where it proved very useful. At the same time, much less attention has been paid to temporal (quasi-) periodicity of dynamic textures, despite the obvious fact that this property is inherent in dynamic texture. We discuss the reasons, then present a framework for quantitative motion periodicity analysis of DTs. Using the optic flow and adapting the SVD-based algorithm for signal period estimation [17], we measure degree of periodicity of natural dynamic textures. Numerous test results are presented, including the application of the temporal periodicity features to DT classification.

1 Introduction

Following the terminology of the pioneering paper [20], three visual motion pattern categories are usually distinguished, namely, motion events, activities, and dynamic (temporal) textures. Individual motion events, like a single opening of a door, possess no temporal or spatial periodicity; they are beyond the scope of this study which is devoted to periodicity analysis. Activities of moving non-rigid objects, like digging, are periodic visual motion patterns localised in space and time. Finally, dynamic textures are spatially repetitive, time-varying motion sequences exhibiting certain temporal stationarity. This stationarity, which assumes temporal repetitiveness, is a basis of most dynamic texture models (e.g., [7]) and methods for DT recognition [6].

Periodicity analysis, which has a long history in applied signal processing [17], has also been fruitful in computer vision. Spatial texture synthesis and recognition [18, 5, 10, 9] and activity detection, segmentation and behaviour analysis (gait, running, jumping, etc.) [24, 2, 8] are probably the best known examples of its application. As pointed out in the studies [5, 24], periodicity facilitates *learning* of the repeating regular pattern, extrapolating the pattern, or detecting irregularities, or abnormal events, within regular data. For learning, accurate detection and alignment of the repeating pattern [24, 9] and estimation of the **period length** are necessary; measuring the **degree of periodicity** is not needed.

This latter circumstance may be one of the reasons why temporal periodicity analysis of dynamic texture has received little attention. Although it is generally recognised that periodicity is inherent in dynamic texture, and it can probably serve as a useful feature

for DT description and recognition, very few attempts to explicitly measure this property are known. The recent survey [6] mentions just a few methods that keep track of DT ‘history’ to a certain, limited temporal depth [3, 11, 21, 22]. With small depth, one can only estimate short-term temporal variations such as acceleration [19]; no periodicity estimation is possible. Global spatiotemporal transforms like spatiotemporal wavelets [25] may become useful in multiscale periodicity analysis when motion periodicity appears at different scales (e.g., trunk, branches, leaves of a tree in the wind). However, such transform should be applied to a large spatiotemporal volume, which has not been done yet.

We are motivated by the challenges of measuring temporal periodicity in dynamic texture: (1) lack on vision algorithms to start/compare with; (2) large volume of the spatiotemporal data to process; (3) non-stationarity of the signals involved; (4) need to measure noisy, low-periodicity signals; (5) need to provide a periodicity measure that behaves consistently and contributes to recognition of real-world DTs.

These challenges cannot be addressed by the methods used in activity recognition; in particular, alignment of the repeating pattern [24, 9] and spatiotemporal salient points [8] are not applicable to smoke, fire, shower, or others DT not composed of well-detectable moving shapes. As we discuss later, Fourier Transform is not a good solution either.

The **contributions** of this paper are as follows. Using optic flow, we adapt the SVD-based algorithm [17] to periodicity estimation, which allows us to measure the degree of periodicity of natural dynamic textures. In doing so, we (1) provide a signal pre-processing procedure that renders the method applicable to a noisy signal riding on a nonlinear trend; (2) introduce different measures and analyse their behaviour at growing noise level; (3) address the issue of periodicity variation within a signal (non-stationarity); (4) compare the SVD-based method to other methods, such as signal minima and zero-crossing analysis; and, finally, (5) apply the introduced temporal periodicity features to recognition of 26 dynamic textures.

2 DT analysis with optic flow

By estimating motion periodicity, we hope to obtain a richer description of dynamic texture and contribute to the solution of different problems related to DT processing and recognition. Beyond the standard tasks of texture analysis for static and dynamic data, such as classification and segmentation, one can also aim at finding a (known or unknown) texture in an image, or dynamic texture in a video. The complementary problem is to find a defect in a texture, or an irregular event in a DT. An example of the latter is searching for an unusual behaviour in a walking crowd. When no prior information is available on the expected properties of the irregularities, this task is essentially outlier detection with learning on the regular majority data. Finally, DT *separation*, that is, separation of partially transparent, overlapping dynamic textures seems to have no analogue on the static side, since this is mainly possible due to motion.

As emphasised in the survey [6], the optic flow based approaches are currently by far the most popular among different approaches to DT description and recognition. We also use optic flow that allows us to concentrate on the *dynamic component* of a DT, which is of primary importance for temporal periodicity analysis. The *appearance component* is less important for us; this component can be added when desired, for example, to use colour and shape for better segmentation. In the current study, we intentionally ignore the

appearance component in order to understand how much information visual motion can provide about the classes of natural and artificial processes captured by videos.

A selection of fast and precise optic flow algorithms is available, ranging from the simple normal flow to the modern implementation [16] of the classic Horn-Schunck procedure [15] and the method [4] that uses more sophisticated spatiotemporal smoothness constraints, as well its extension [1] that applies pre-segmentation to better respect motion discontinuities. As demonstrated in the study [12], the choice of optic flow algorithm is a critical issue when temporal textures are processed. It is more critical here than in the case of large moving objects because of numerous fine details in motion and more frequent discontinuities and occlusions.

A related important issue is that of measuring the *confidence* of the optic flow values. In the studies [19, 12], the confidence measure proposed in [14] was used to weigh the contribution of a pixel to an optic flow statistics. It was demonstrated that the weighting results in better classification rates, which can be attributed to an efficient removal of flow outliers as well as the pixels where the flow cannot be calculated due to the lack of motion information. In particular, the confidence measure [14] is composed of the eigenvalues of the spatiotemporal structure tensor and reflects its rank. The rank should be two for unambiguous calculation of flow; other values mean no apparent motion, the aperture problem, or flickering.

In this study, we test several algorithms for optic flow and two different confidence measures. Besides the described one, we also test a new confidence measure that will be presented in detail in a forthcoming paper. The idea is to roughly pre-segment the image based on the *warping error* between frames F_k and F_{k+1} : we warp back pixels in F_{k+1} by the flow, then calculate the difference between warped values and F_k . The warping error is an indicator of a dynamic texture, with its frequent discontinuities and occlusions.

3 Periodicity estimation

In the rest of the paper, we will assume that an accurate optic flow has been calculated using the above mentioned methods, and the *average flow magnitude* in each frame has been computed as a function of time, or frame index, resulting in a one-dimensional temporal signal. (We will consider other flow features in future research.) From now on, we will deal with such signals and speak of signals rather than images.

In this section, we present several algorithms for signal periodicity estimation. The core of the section is the method by Kanjilal, Bhattacharya and Saha [17] which we adapt to our needs. Originally, this method was designed for *period length estimation* of quasi-periodic time-varying data such as medical signals (ECG, EEG), global temperature time series, solar activity, electrical power load pattern in urban areas, and many others. For us, the period length is less important, as we focus on *periodicity measurement*. We will demonstrate that the method [17] can be used for this purpose as well.

To better illustrate our goals, let us jump for a moment to some numerical results of the algorithm we are going to present now. Imagine we are generating a sequence of digital signals with growing Gaussian noise added to the amplitude, as shown in figure 1. The initial signal is periodic with the period length 25. When $\sigma_{noise} = 1.0$, one can hardly recognise any periodicity in the deteriorated signal. Still, we expect the method to measure the periodicity and the period, and it actually does: figure 2 demonstrates that this is

possible. Below, we explain how the basic SVD-based method works.

3.1 The basic SVD method

As discussed in [17], a (nearly) periodic signal has three periodicity attributes: (1) period length; (2) pattern over successive repetitive segments; and (3) scaling factors associated with repetitive segments. Note that a periodic component embedded in a signal may not be sinusoidal and may contain segments that scale differently.

Using the notation of [17], consider a digital signal $x(k)$. Assume that the period is n and place the successive n -intervals of $x(k)$ into the rows of the $m \times n$ data matrix

$$A_n = \begin{bmatrix} x(1) & x(2) & \dots & x(n) \\ x(n+1) & x(n+2) & \dots & x(2n) \\ \dots & \dots & \dots & \dots \\ x((m-1)n+1) & \dots & \dots & x(mn) \end{bmatrix} \quad (1)$$

If n equals the period length, the rows of A_n are linearly dependent, even when the scaling factors of the rows are different. The method uses the robust Singular Value Decomposition (SVD) to test the ‘rank oneness’ of the matrix A_n and determine the repeating pattern and the scaling factors.

Applying SVD, we decompose the data matrix as $A_n = USV^T$, where $UU^T = U^T U = I$, $VV^T = V^T V = I$. The diagonal matrix S contains the sorted singular values: $S = \text{diagonal}(s_1, s_2, \dots, s_r : 0)$, $s_1 \geq s_2 \geq \dots \geq s_r \geq 0$, with the rank $r = \min(m, n)$. The left (right) singular vectors u_i (v_i) are the columns of U (V), respectively.

The meaning of the decomposition is the following. For *strictly periodic* $x(k)$ with period N , $x(k) = x(k+N)$ and $\text{rank}(A_n) = 1$ when $n = N$. In this case, $s_1 > 0$, $s_2 = s_3 = \dots = s_r = 0$; $s_1/s_2 = \infty$. The vector v_1 is the (normalised) periodic pattern, the elements of $u_1 s_1$ are the scaling factors; here, they are all equal. For *nearly periodic* $x(k)$ with period N , but $x(k) \neq x(k+N)$, two cases are possible: (1) same repeating pattern, but with different scaling; (2) nearly repeating patterns, with different scaling. In case (1), $\text{rank}(A_n) = 1$ for $n = N$, $s_1 > 0$, $s_2 = s_3 = \dots = s_r = 0$, and $s_1/s_2 = \infty$. The vector v_1 is still the periodic pattern. In case (2), the matrix A_n can be full-rank, and $s_1 \gg s_2$.

Summarising, $s_1 \gg s_2$ indicates a strong primary periodic component of the length n , given by rows of the matrix $u_1 s_1 v_1^T$. To obtain the further component, one can iterate the above procedure for the residual matrix $A_n - u_1 s_1 v_1^T$.

The study [17] defines the periodicity spectrum (P-spectrum) as the variation of the ratio s_1/s_2 with n . Considering the dominant maxima of the P-spectrum at $n = N, 2N, 3N$, etc., one selects N with the highest maximum count as the most probable value of the period length. (See [17] for technical details.) Following the same basic idea, we consider two alternative **measures of signal periodicity**

$$P_1 = 1 - \frac{s_2}{s_1} \quad \text{and} \quad P_2 = \frac{s_1 - s_2}{s_1 + s_2}, \quad (\text{low}) \quad 0 \leq P_1, P_2 \leq 1 \quad (\text{high}) \quad (2)$$

and analyse their efficiency on various data. Before doing this, however, we need to introduce some additional steps that render the method applicable to dynamic texture.

3.2 Modification for real DT signals

By a DT signal we mean temporal variation of the average optic flow of a dynamic texture. Figure 5a shows an example of such signal for a low-periodicity DT. This is certainly not the signal one dreams of when working on signal periodicity. The signal rides on a strong nonlinear trend, and its periodicity, if any, may be changing, leading to non-stationarity. The above described basic algorithm is not applicable to such signals, as it cannot cope with varying mean level and non-stationarity: it can only cope with varying amplitude, assuming that scale is largely constant within a segment. These problems should be addressed keeping in mind that SVD is sensitive to shift of signal level.

Three **pre-processing** algorithms are applied to reduce the effects of noise, signal trend and amplitude variation: (1) the signal is smoothed by a small mean filter to remove noise; (2) the denoised signal is detrended by smoothing it with a large mean filter, then subtracting the result (the mean level) from the denoised signal; (3) the detrended signal is normalised without shifting. Figure 5b shows the result of pre-processing the original signal (a). Some periodicity, although low, is now visible.

After the pre-processing, the basic algorithm presented in section 3.1 is applied. However, it is not applied to the entire signal at once. To cope with potential **non-stationarity**, data windowing is used. A data window slides over the signal, and for each data window position the basic algorithm computes the periodicity defined in eq. (2). To decrease the sensitivity of the method to the starting point within a data window, one can average the result over a range of starting points. In practice, we simply smooth the result of data windowing (periodicity versus window position) by yet another mean filter. As suggested in [17], the size of data window should span at least four periods of the signal.

We use the fast modified Golub-Reinsch algorithm implemented in C++ in the GNU Scientific Library (GSL) available at [13]. The complete processing of a DT signal of length 250 takes less than one second on a 3GHz machine. This is less than the time needed to compute the signal from a DT sequence of this length by any flow technique.

3.3 Other possibilities of periodicity estimation

The study [17] provides arguments and numerous tests in favour of the authors' opinion that, in signal periodicity estimation, SVD is superior to FFT on real quasi-periodic data. Many synthetic and real signals, from very different applications, are processed with both methods and compared to justify the claim.

Without going into details, we can summarise the conclusions of [17] as follows. FFT decomposes a signal into sinusoidal patterns (harmonics) of infinite length. Each pattern has a fixed scale. FFT is likely to miss the prime periodicity when (a) the actual optimal pattern varies from sinusoidal pattern of same length, and/or (b) scaling over successive repetitive segments is different, and/or (c) the noise is strong. The superiority of SVD stems from the following: (a) SVD can cope with any form of the repeating pattern; (b) it can cope with different scaling; and, finally, (c) it provides the most robust rank assessment (nearness to rank one).

Accepting the outcome of the comprehensive study [17], we did not include FFT in our tests. Since it is desirable to compare the SVD method to another approach, we designed and implemented two other, simpler methods based on measuring the distances between signal minima or zero-crossings (ZCs). The rationale behind focusing on the

dominant minima is that the periodicity of a dynamic texture is often perceived due to the turning points of the optic flow: the flow stops, then moves back.

The *minima-based algorithm* receives the same pre-processed and normalised signal as the SVD-based one. First, dominant minima are detected as the turning points of the flow. Then, we accumulate the histogram of distances between consecutive minima and remove the outliers using the alpha-trimmed filter that discards the lowest 20% and the highest 20% of the distance spectrum. In the remaining distance histogram, the mean is taken as the period. The mean absolute deviation from the period is divided by the period, to serve as a *measure of randomness*, as opposed to periodicity. To cope with non-stationarity, the same data windowing procedure is used as in the SVD case.

Zero-crossings are closely related to minima. For completeness, they have also been tested. The only difference is that here the histogram accumulates the distances between the second nearest, rather than consecutive, zero-crossings.

4 Experimental results and conclusions

Tests with **generated signals** were carried out in order to (a) compare the two periodicity measures defined in eq. (2), and (b) analyse the robustness of periodicity estimates by SVD, minima and zero-crossings. Examples of synthetic signals generated with additive Gaussian noise are shown in figure 1. As σ_{noise} approaches 1.0, the noise amplitude exceeds that of the original signal, and periodicity seems to completely disappear. One can observe in figure 2 that this is roughly the point when the *period length* estimation by SVD becomes unstable and imprecise. At the same time, the *periodicity* plots demonstrate correct behaviour for both measures. In our further experiments, we use P_1 because of the more gradual and linear decrease of the periodicity with σ_{noise} . However, P_2 can also be used.

Figure 1: Examples of signals generated with growing amplitude noise. Period is 25.

Figure 2: SVD estimates of periodicity and period length for growing σ_{noise} .

Figure 3 presents plots of periodicity (i.e., 1-randomness) and period length estimates by the minima algorithm and the ZC algorithm. The latter yields a more robust period length estimate than the former. (Note that the two σ_{noise} ranges are different!) However, the ZC algorithm yields a very narrow range of periodicity values, which makes it practically unusable for periodicity estimation. In this respect, the minima method is somewhat better. Both minima and ZC are clearly inferior to SVD on this kind of synthetic data.

Figure 3: Periodicity and period length estimated with minima and zero-crossings.

Tests with real **DT signals** were done using the DynTex database [23]. Figure 4 shows selected frames of four dynamic textures from the database, while figures 5–8 illustrate the processing of the four DT signals and show the resulting plots of periodicity versus data window position, $P_1(k)$. Two periodicity features are computed and presented in table 1: the average periodicity over all data windows $\langle P_1 \rangle$ and the relative absolute variation δ_{rel} . The estimated values are generally consistent with our expectations concerning the character and the ordering of periodicities for the four DTs. In particular, the two views of an escalator differ in periodicity because the close view (a single step) is much more stable. The optic flow in the distant view varies considerably as the white painted step enters the viewfield, grows, then leaves. These variations are reflected by the periodicity plot in figure 7c.

Figure 4: Selected frames of four dynamic textures from DynTex database.

Figure 5: Processing dynamic texture Leaves.

Figure 6: Processing dynamic texture Danube.

Figure 7: Processing dynamic texture Escalator.

Finally, table 2 demonstrates that periodicity can be helpful in dynamic texture classification. The classification test uses the same 26 DTs from the DynTex database and the same optic flow features as the study [12]. However, the experimental protocol is different, as in the current study the sequences are divided in space to obtain samples, while in [12] they are divided in time. (We had to use spatial division to keep signals long enough for periodicity analysis; for this reason, no direct comparison to [12] is possible.) Table 2 shows that classification rate improves consistently when two periodicity features, $\langle P_1 \rangle$ and the average minima randomness, are added to the 16 original optic flow features introduced in [12]. In particular, the BBPW optic flow [4] yields the best result when no confidence measure is used; the result improves by almost 4% when periodicity is added. For the Haussecker confidence measure [14], the gain is almost 4%. The best classification rate of over 95% was achieved with periodicity using the CVHS flow [15, 16] and the warping error confidence. Of the two periodicity features useful for classification, most of the gain can be attributed to the SVD feature.

To summarise, we conclude that SVD-based estimation of temporal *periodicity* of dynamic texture is feasible. For successful application, signal pre-processing, normalisation, and data windowing are essential, as many DT signals are non-stationary. Our preliminary experience shows that *period length* estimation in real data is not sufficiently robust. Concerning DT classification, we observed that the range of DT periodicities in the DynTex database is quite narrow, and the classes may overlap. Our tests show that

dynamic texture	periodicity $\langle P_1 \rangle$	variation δ_{rel}	characteristic
Leaves	0.293	0.067	low, stable periodicity
Danube	0.461	0.069	mid-range, stable periodicity
Escalator	0.477	0.152	rather high, varying periodicity
Escalator Step	0.716	0.033	high, very stable periodicity

Table 1: Average periodicities and relative variations.

Figure 8: Processing dynamic texture Escalator Step.

conf. measure	optic flow	without per.	with per.
none	BBPW	79.8%	83.7%
Haussecker	BBPW	85.6%	89.4%
warp error	CVHS	92.3%	95.2%

Table 2: Classification results for 26 DTs from DynTex.

SVD periodicity is useful in DT classification, but one should not expect too much. The other two methods for periodicity estimation we tested are less efficient, because both are sensitive to noise; in addition, zero-crossings are too sensitive to signal level variation. SVD may be sensitive to multiple periodic components and to period length variation. Further research is needed on a larger database with longer signals, where more periods can be observed. The method is invariant to rotation and scaling in the image plane. To achieve affine invariance, other flow features should be considered.

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